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Including operational aspects in the planning of power systems with large amounts of variable generation

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Article Title: Including operational aspects in the planning of power systems with large amounts of variable generation: a review of modelling approaches

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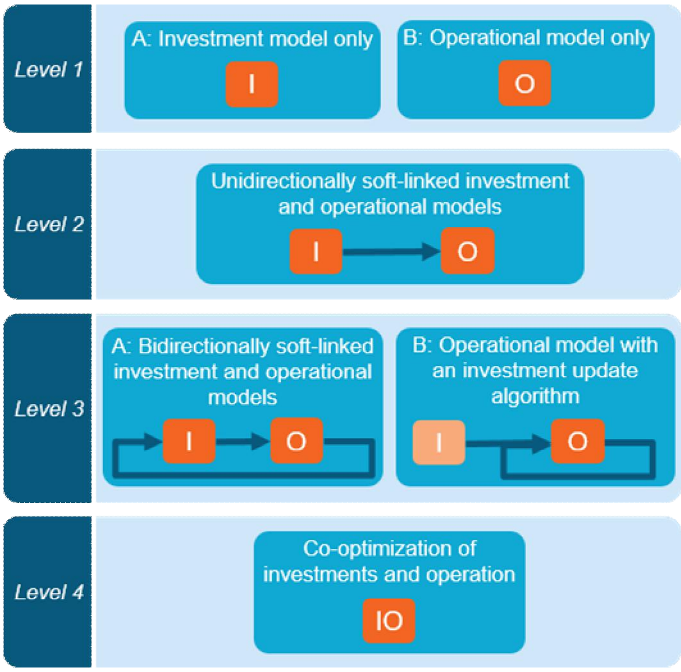
Abstract

In the past, power system planning was based on meeting the load duration curve at minimum cost. The increasing share of variable generation makes operational constraints more important in the planning problem, and there is more and more interest in considering aspects such as sufficient ramping capability, sufficient reserve procurement, power system stability, storage behaviour, and the integration of other energy sectors often through demand response assets. In variable generation integration studies, several methods have been applied to combine the planning and operational timescales. We present a four-level categorization for the modelling methods, in order of increasing complexity: 1a) investment model only, 1b) operational model only, 2) unidirectionally soft-linked investment and operational models, 3a) bidirectionally soft-linked investment and operational models, 3b) operational model with an investment update algorithm, and 4) co-optimization of investments and operation. The review shows that using a low temporal resolution

or only few representative days will not suffice in order to determine the optimal generation portfolio. In addition, considering operational effects proves to be important in order to get a more optimal generation portfolio and more realistic estimations of system costs. However, operational details appear to be less significant than the temporal representation. Furthermore, the benefits and impacts of more advanced modelling techniques on the resulting generation capacity mix significantly depend on the system properties. Thus, the choice of the model should depend on the purpose of the study as well as on system characteristics.

Graphical/Visual Abstract and Caption



Energy and power system models can be categorized into four levels based on the complexity captured in terms of planning and operation.

INTRODUCTION

Power systems can play a crucial role in de-carbonizing energy systems as they can relatively easily integrate large amounts of renewable generation. However, the increasing amount of wind and solar power, as well as other forms of variable generation (VG), has a strong impact on the operation of power systems through the variability and uncertainty of wind speed (Wu et al., 2017) and solar radiation (Ueckerdt, Brecha, & Luderer, 2015). There are also system-wide impacts like low system inertia (O'Sullivan et al., 2014) and ramping requirements (Denholm, O'Connell, Brinkman, & Jorgenson, 2015). Conventional power plants, also those low in the merit order, will need to start up and ramp more frequently. Demand response and different forms of energy storage will become increasingly relevant to aid in the shaping of supply and demand to match one another at all time points. VG is also changing the way power systems are operated – regulations concerning reserve procurement, market gate closures and use of stochastic information are evolving to better reflect the changing system composition (Kiviluoma et al., 2012). In order to understand these phenomena, more comprehensive scheduling models have been developed, and they have been used to find better practices to operate future power systems.

Improving operational models is not enough, power system planning also needs to evolve. In the past, many operational constraints were often not considered, or they were grossly simplified, to keep the planning models computationally small. Historically, the most relevant objective in planning has been to meet the load duration curve at minimum cost, whereas nowadays there is an increasing interest in considering also the capacity value of alternative supply sources, some aspects of power system stability, sufficient ramping capability, sufficient reserve procurement, storage behaviour and the integration of other energy sectors often through demand response assets. The increasing share of variable power generation is making other operational constraints more and more important for the planning stage, and this is also the focus of the present review: generation planning from the perspective of including operational detail. The inverse can also be important: how to provide good future scenarios for the study of future power system operations, but this viewpoint will not be brought forth in the article.

Several reviews have been conducted in the literature on the use and development of models for both power system operational scheduling and power system planning with high shares of VG. On the operational side, the report on the recommended practices for wind integration studies (Holttinen et al., 2013) highlights how to capture the impact of wind and solar by modelling the flexibility options and their limitations, and how to ensure representative input data for wind and solar variability and uncertainty. Likewise, a report by IRENA (2017) presents practical VG modelling methodologies for long-term scenario planning. This modelling need has significantly increased the computational resources required for accurate modelling. Consequently, there has been an arising interest to accurately consider operational constraints within the planning problem.

Meanwhile, a detailed framework to quantify operational power system flexibility including metrics and properties is presented in (Ulbig & Andersson, 2015), where the authors provide an intertemporal view of the different flexibility requirements. The authors further analyse the different sources of flexibility and technological alternatives to provide the system with resources to mitigate power fluctuations coming from VG. Discussion on the modelling of flexibility issues, the linkage of energy system models and sector-detailed energy models, and the representation of flexibility needs in power system models has been compiled in (Hidalgo González et al., 2015).

On the other hand, there are existing categorizations and reviews covering different energy and power systems expansion models, albeit often focusing more on the energy system perspective than on the power system side. A review of the typology of energy modelling tools can be found in (Després, Hadjsaid, Criqui, & Noirot, 2015), with the objective to see how the characteristics of the power sector are integrated into the broader energy modelling tools. Pfenninger, Hawkes, and Keirstead (2014) reviewed current energy system modelling paradigms and challenges. The authors grouped the models into four categories (energy systems optimization models, energy systems simulation models, power systems and electricity market models, and qualitative and mixed-methods scenarios) as well as examined approaches to overcome four challenges that the models face (resolving time and space, balancing uncertainty and transparency, addressing the growing complexity of the energy system, and integrating human behaviour and social risks and opportunities).

Collins, Deane, Poncelet, et al. (2017) discussed the characteristics of unit commitment and economic dispatch (UCED) models, energy system optimization models (ESOMs) and integrated assessment models (IAMs), and reviewed methodologies to integrate short-term variations of the power system into the models in the last two categories. Poncelet, Höschle, Delarue, Virag, and D'haeseleer (2017) focused on improving the temporal representation in ESOMs and generation expansion planning (GEP) models. Generation expansion planning was in focus also in (Oree, Sayed Hassen, & Fleming, 2017), which discussed early environmental considerations, managing conflicting objectives, and uncertainty handling, but also integration of VG from capacity adequacy and operational flexibility point of view. Supplementary Table 9 of (Zeyringer, Price, Fais, Li, & Sharp, 2018) gives an overview of the spatial and temporal resolution as well as the energy sectors covered in a number of VG integration studies.

This paper discusses operational and planning models, to be used in tandem for studying future power systems with higher shares of wind and solar generation. The focus is on operational constraints in planning. The review deals with system-wide approaches, and models intended for microgrid or local analysis are not discussed. More precisely, we consider approaches emerging from the combination of three model families: ESOMs, GEP models and UCED models. While these model types have long been based on rather distinct methodologies, they are today approaching the same all-inclusive target from different angles: recently, efforts have been made to improve the temporal and operational representation of ESOMs, to take into account more energy sectors and a more detailed description of individual units in GEP models, and to consider investment variables in UCED models. In addition, several approaches have been presented to soft-link two or more model types together, using unidirectional or bidirectional soft-linking.

In this paper, we first present a classification of current challenges in the modelling of the planning problem. Then, we describe the characteristics and purposes of the traditional ESOMs, GEP models and UCED models and present a categorization for approaches to combine operational constraints in the planning stage. To our knowledge, a similar categorization has not been presented in the literature. The purpose of the categorization is to add value by making the differences between modelling approaches more explicit for existing and future studies. After the classification of modelling challenges and the categorization of modelling approaches, we perform a review of recent VG integration literature based on both the modelling challenges and the modelling approaches. Figure 1 outlines the structure of the paper.

Many energy and power system models published in the academic literature are theoretically capable of modelling various features from short-term to long-term behaviour. However, in practice these features are rarely considered simultaneously. Instead of possible use of different models, we review methodologies applied in VG integration studies, and the strengths and limitations of different approaches are discussed. Based on the selected studies, the article shows how the representation of operational details can impact the model outcomes.

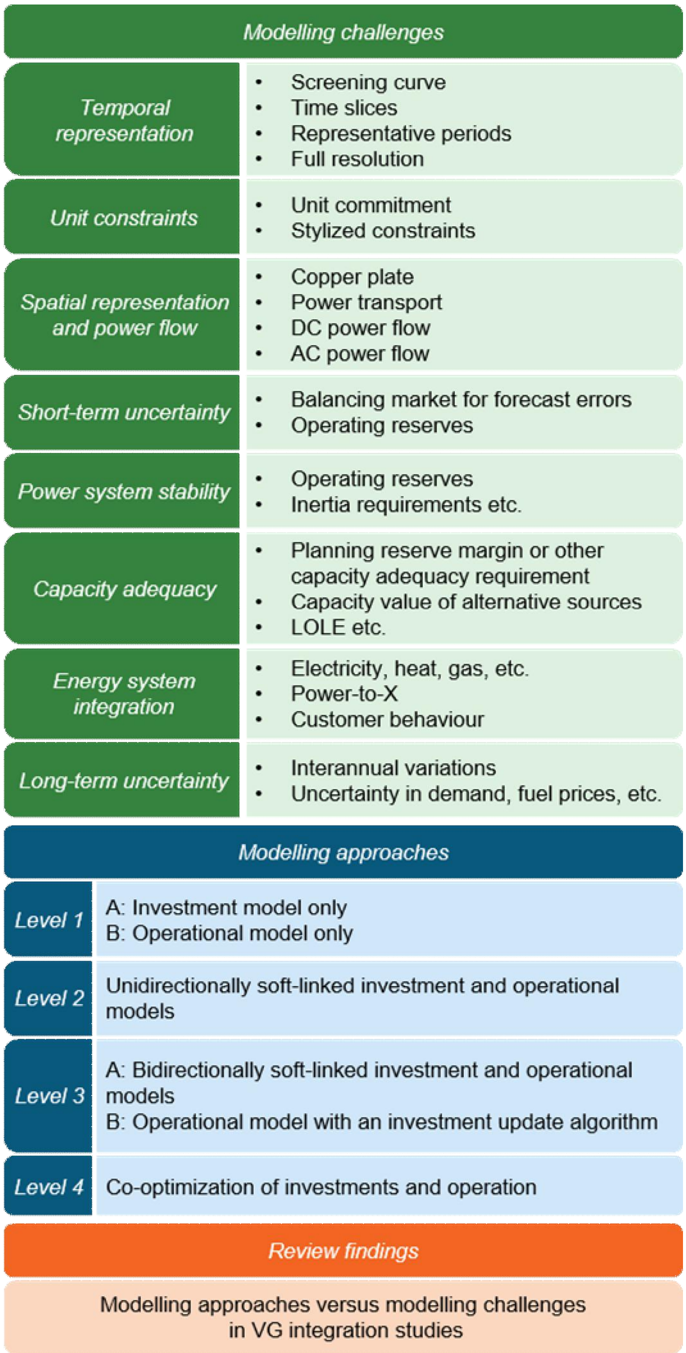


Figure 1 Paper structure

MODELLING CHALLENGES

Combining planning and operational modelling involves several challenges, including choices on how to consider temporal and spatial detail, unit commitment (UC), power flow, generation and load forecast errors, system stability, capacity adequacy, sector interactions, as well as long-term uncertainties.

Temporal representation

Representation of temporal variability plays an important role in investment models, and the effects of different representations have been investigated in literature (Merrick, 2016), (Poncelet et al., 2017), (de Sisternes & Webster, 2013). It is especially important to consider certain aspects when selecting the temporal representation in the model. First, it is important to keep natural correlations of load, wind speed and solar irradiation. Second, retaining short-term chronology is necessary to capture the flexibility needs arising from the variability of load and renewable power production. For example, it is impossible to properly evaluate the benefits of storages if chronology is not retained in the modelling. It has also been shown that neglecting chronology can significantly affect generation expansion planning results (Nweke, Leanez, Drayton, & Kolhe, 2012). Third, a sufficient temporal resolution is needed.

There are principally four approaches to represent temporal variations in investment and operational models, as depicted in Figure 2 (see examples in Table 1–Table 4):

1. The representation can be based on the screening curve method, which is the simplest approach. It utilizes the load duration curve or the net load duration curve. Net load is determined by subtracting variable generation from the load, and the result is sometimes called the residual load. This method does not retain chronology.

2. The representation can also be based on time slices. This method tries to define a year using a number of periods – the so-called time slices – typically based on seasonal, weekday-weekend and day-night variations. Depending on how the time slices are defined, it is possible to retain some of the chronology. However, chronology is not preserved in the so-called integral method, which is the most common method to assign values to the time slices (Poncelet, Delarue, Six, Duerinck, & D'haeseleer, 2016).

3. As chronological data is a prerequisite to model several energy system flexibility options, an alternative approach to deal with the temporal variations is to use representative periods. In this method, a set of days or weeks is selected from the historical time series to represent a year. It is common to select a period from each season or each month and some extreme periods, such as the peak load day or week. These representative periods retain chronology within themselves but not necessarily between themselves.

4. The most precise approach is to use full hourly or sub-hourly resolution. This way full chronology inside an entire year or multiple years is preserved.

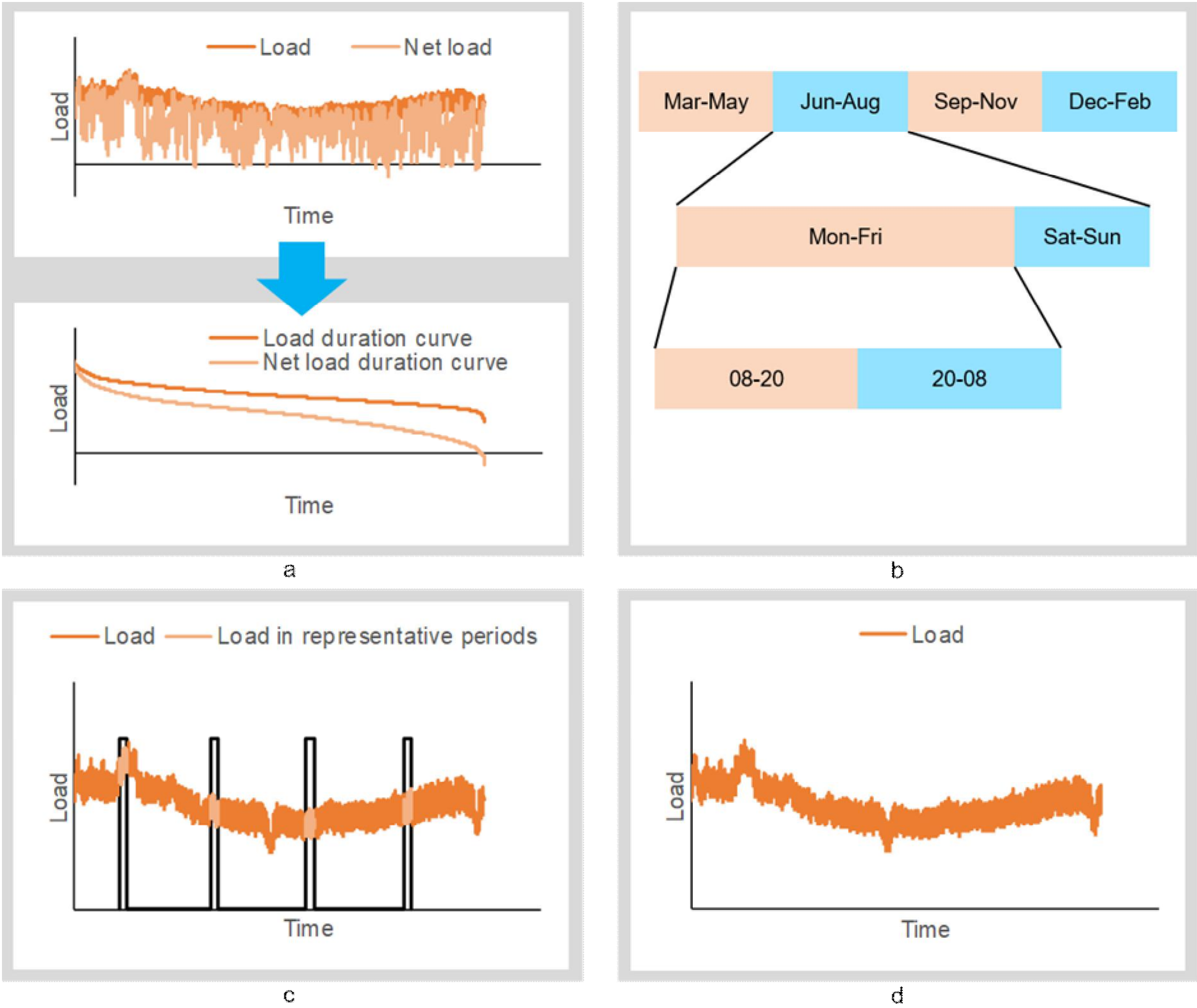


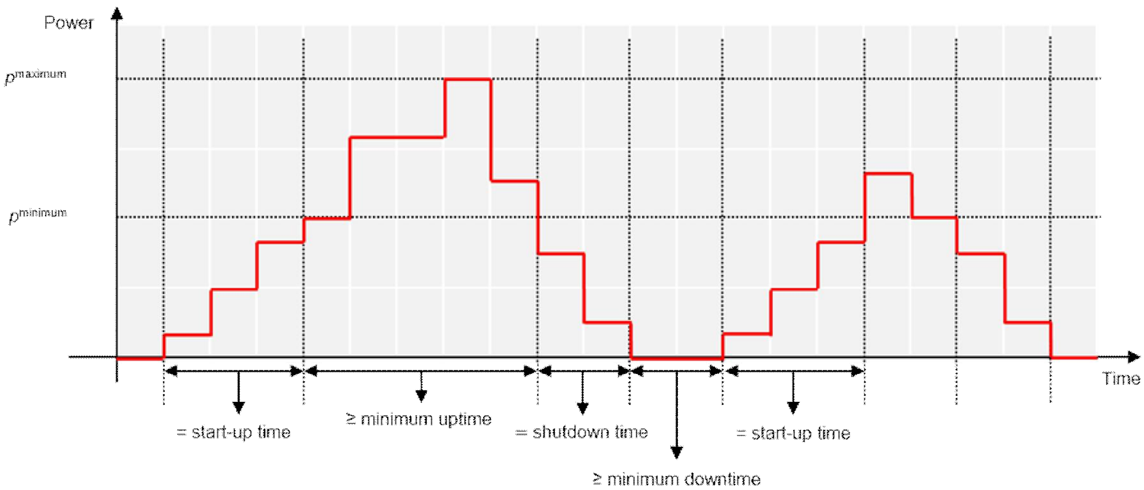
Figure 2 Four approaches to represent temporal variations over a year. (a) Screening curve method where chronological time series are converted to load duration curve or net load duration curve. (b) An example of the time slice approach with 4 seasonal, 2 weekday-weekend and 2 day-night time slices (altogether 16 time slices). (c) An example of the representative period approach with 4 selected weeks (shown inside black rectangles). (d) Full chronological time series. (Scaled load and wind power data from Finland 2011.)

Both the time slice approach and the representative period approach utilize appropriate weighting in order to represent the relative prevalence of the time slices or representative periods during a year. When defining the time slices or selecting the representative periods, the modeller needs to recall that different systems may require different criteria. For example, in some systems seasonal variations are more important than in others, and in hydropower-dominated systems, the difference between wet and dry years is important. In addition, the lack of chronology between representative periods may be an issue for long-term storages, and it may be necessary to implement additional constraints in order to consider the evolution of storage state between the periods appropriately.

It has also been recognized that approximations made in traditional UCED model formulations, such as using a stepwise energy profile, can result in suboptimal or even infeasible schedules for slow-start thermal units and inaccurate predictions of actual costs. One solution to partially overcome these issues is to use piecewise-linear power profiles of generation and load (Morales-España, Ramírez-Elizondo, & Hobbs, 2017). These observations could also be applied to the development of investment models.

Unit constraints

The operation of generation units is constrained by maximum and minimum generation levels, part-load efficiency reductions, ramping limits, minimum uptimes and downtimes, and different start-up and shutdown stages. Figure 3 shows an example of the operating stages of a thermal unit in a unit commitment problem. Start-ups can be divided into cold, warm and hot start-ups and they are associated with different costs and fuel consumptions. Ramping also induces costs. Furthermore, maximum and minimum storage states need to be considered for units with storage capacity. Start-ups, ramping limits and storage states cannot be accurately modelled without short-term chronology.



t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Online variable	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0
Start-up variable	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Shutdown variable	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0

Figure 3 An example of the representation of thermal unit operating stages

Energy and power system models can include online, start-up and shutdown variables to consider the commitment state of units. These variables can be binary when the units are modelled separately, but the computation burden can be reduced by aggregating units based on similar technology. This leads to integer variables. To reduce the complexity further, the variables can be relaxed to continuous variables. However, the simplifications have impact on the accuracy of the results.

The term 'unit commitment' can be used to denote the decision to start up and shut down units with uncertain information about the future. Considering traditional electricity market gate closures, this can also be referred to as day-ahead unit commitment. For some units, the start-up decision has to be made well in advance, but there are also units which can start up very fast. Thus, as unit commitment can be adjusted closer to real-time, modelling unit commitment can also denote that the model is allowed to optimize start-up and shutdown decisions in general, also in the case of perfect foresight models. The opposite would mean omitting start-ups and shutdowns completely, or giving the commitment state as a parameter to the model. For example, some of the units can be set as must-run units by specifying their online status to be always true.

Spatial representation and power flow

The spatial detail of the model impacts the representation of variable renewable energy sources and power grid constraints.

Variable renewable energy sources vary in time and space, and results have shown that geographical disaggregation of wind energy resources can significantly affect the outcomes of an energy system model (Simoes et al., 2017). However, the relevance of geographical disaggregation depends on several factors, including the cost-effectiveness of wind power: when wind power was very cost-effective, its potential was reached regardless of the level of spatial disaggregation. Furthermore, there are several socio-environmental siting restrictions that shape the potential and deployment of variable renewable energy sources, including acceptable distances to residential and other land use functions as well as nature reserves and other such areas. However, it is not only the land use restrictions that shape the wind resource potential – also the chosen wind turbine technology can have a significant impact (Rinne, Holttinen, Kiviluoma, & Rissanen, 2018).

High amounts of wind and solar power increase long-distance transmission and change the general power flows, and it is thus important to accurately consider power grid bottlenecks and other grid constraints in the modelling. On the other hand, transmission links are a great source of flexibility as they can be used to smooth out the variability of wind power over a large geographic area. Power grid bottlenecks have an impact on how much flexibility is needed in different parts of interconnected power systems and they also limit how much the flexible resources in neighbouring areas can help. This also calls for an adequate grid representation.

The level of detail in the grid representation is affected by the choice between a nodal model and a zonal model. In nodal models, grid nodes are modelled separately and it is possible to represent physical transmission lines explicitly. In zonal models, grid nodes are aggregated into zones connected by critical network elements. Calculating the power flows on these critical network elements requires aggregated network parameters. The calculation of these parameters has been discussed in the Nordic context in (Energinet.dk, Svenska Kraftnät, Fingrid, & Statnett, 2014).

On the other hand, grid representations in energy system models can be divided into four categories depending on the simplification level of the power flow calculation method: copper plate models, transport models, linearized (DC) power flow models, and full (AC) power flow models (see examples in Table 5–Table 8). These require different amounts of data for the grid representation and different amounts of computational power:

1. Copper plate models do not consider grid bottlenecks at all and they do not require any data of the grid topology.

2. Transport models represent grid bottlenecks by constraining exchanges between regions to net transfer capacities (NTCs). NTCs can be calculated through more detailed power system analysis in order to take into account both the thermal limits of the transmission lines as well as the power system stability constraints. Transport models only consider commercial power trade and ignore physical power flow principles.

3. DC power flow models consider not only the maximum capacities of the transmission lines but also Kirchhoff's law by taking into account the reactance of the transmission lines. DC power flow models only consider active power flows and the resulting active power flows are approximations.

4. AC power flow models represent AC grids more realistically by taking into account both active and reactive power flows as well as voltage deviations. AC power flow models require more detailed data of the transmission lines (i.e. the so-called Pi-model including line reactance, line resistance and line charging susceptance).

In many investment and operational models, DC power flow is assumed to represent power flow constraints of synchronous links suitably. Unlike power flows in synchronous links, power flows in asynchronous links are controlled and they can be represented using the transport model. The same applies for radial synchronous links as well.

VG integration studies often focus on only one country (see examples in Table 1–Table 4). However, it is important to consider what happens at the boundaries of the modelled region, assuming that the system has significant transmission links in relation to its size. Export and import outside the modelled region can have a significant impact on the results. The question remains when adding more countries to the study: even when modelling the four countries in the Nordic synchronous system and five other countries surrounding it, ignoring transmission links to countries outside the modelled region may lead to misestimation of the flexibility need (Helistö, Kiviluoma, & Holttinen, 2018).

Short-term uncertainty

Short-term energy system uncertainties include most prominently wind, solar, and load forecast errors. As the share of wind and solar power increases, so do the forecast errors that need to be balanced. In real power systems, forecast errors are handled by intraday and balancing markets as well as by reserves, exact methods depending on the jurisdiction. Forecast errors are very dependent on the forecast horizon and spatial aggregation. In ERCOT area in US, monthly mean absolute percent errors for hour-ahead wind forecasts have varied mostly between 3% and 5% in recent years, whereas for PV, forecast errors have been 5–7% between August 2017 and April 2018 (Du, Steffan, Mago, & Sharma, 2018). In Southwest Power Pool in US, 4-hour-ahead errors for load have stayed between 1% and 2% in recent years, while for wind power they have mostly been 3–6% (Miller & Gray, 2018).

For this discussion we categorize reserves into primary, secondary and tertiary reserves. From the different reserve categories, tertiary reserves are the ones used for handling generation and load forecast errors remaining after intraday, and are also handled by real-time or balancing markets. Primary and secondary reserves are used for handling sub-hourly variability and disturbances.

According to a recommended practices report, a comprehensive wind integration study should use detailed input data on wind and load uncertainty (Holttinen et al., 2013). This can be managed in the operational timescale by including reserve procurement and utilization through a simulation of intraday and balancing markets using rolling planning (Meibom *et al.*, 2011), but this day-ahead unit commitment will be much more challenging for the planning problem. It has been shown that including uncertainty in the planning stage can change the planning results considerably at least in stylized cases (Pineda & Morales, 2016). However, including actual presentation of short-term uncertainty in the planning stage will cause a very large computational overhead. Consequently short-term uncertainty is typically reduced into a reserve requirement (De Jonghe *et al.*, 2011), (Jin, Botterud, & Ryan, 2014). However, the devil is in the details. Tertiary reserves can be utilized to mitigate forecast errors during the real-time dispatch and consequently they should be available for utilization by the perfect foresight planning model. On the other hand, if the generation planning model considers only sub-time resolution reserves, it will miss the cost of utilizing tertiary reserves at a short notice.

Power system stability

In the past, power system stability was based on large synchronous generators connected to strongly meshed transmission networks. Today, power generation relies increasingly on wind and solar power plants, which are typically connected to the grid through power converter devices, i.e., they provide non-synchronous generation. In addition, they may be connected to the distribution network or weaker parts of the transmission network, their control capabilities may be different from conventional generators, and their generation is subject to variability and uncertainty. Thus, large VG shares have an impact on the dynamic characteristics of power systems and consequently on power system stability. (Flynn et al., 2017; Holttinen et al., 2011; Shah, Mithulananthan, Bansal, & Ramachandaramurthy, 2015)

Power system stability is essentially a single complex problem, but as the system instabilities can occur in various forms, there has been a need for power system stability classification based on the main system variable where the instability can be observed and the size of the disturbance considered (Kundur et al., 2004). According to various case studies and observations reported in (Flynn et al., 2017), large VG shares may have an impact on all the main stability categories (frequency stability, voltage stability, and the two types of rotor angle stability: transient stability and small-signal stability), but the impact is not necessarily always negative. Assessment of stability requires dedicated power system analysis tools capable of taking into account reactive power and performing dynamic simulations over a timeframe of seconds or minutes. Without sufficient power system stability, disturbances can result in a blackout. Although the complexity of stability assessment has limited its direct incorporation in the investment models and operational models considered in this paper, some simplifications can be made in order to consider part of the stability aspects using these models.

Requirements for primary and secondary frequency reserves can be included in the model to partially consider frequency stability requirements. Primary and secondary reserves are activated in seconds and minutes (primary reserves often in seconds and secondary reserves often in minutes), and any power plants that are capable of changing their output within the required time frame can usually participate in reserve provision and receive remuneration. However, power systems also require even faster responses in order to maintain frequency stability. This can be achieved through synchronous inertia, which is a property of synchronous generators with large synchronously rotating masses. At high instantaneous VG shares, non-synchronous generation units reduce the number of conventional, synchronous units online, and consequently, the amount of synchronous inertia. Thus, additional constraints for the minimum amount of inertia or the maximum instantaneous share of non-synchronous generation may be needed in investment and operational models (Collins, Deane, & Ó Gallachóir, 2017). On the other hand, modern wind turbines can provide fast frequency response emulating the inertial response of synchronous generators using the momentum of the rotor to increase generation for a short while. Furthermore, both wind turbines and PV can be de-rated (operated below possible generation) so that they can participate in upward reserves. While inertia levels and non-synchronous share are convenient stability indicators at low VG shares, more sophisticated measures may be required at higher VG shares. These stability requirements also lead to interaction with curtailment levels. (Flynn et al., 2017)

Some of the other stability issues can be handled in the models by using stylized constraints, for example, by requiring that a certain number of conventional units always need to be operational in certain parts of the system. However, these are conservative assumptions and as the capabilities of wind and solar power plants evolve and new technologies become available, new solutions are needed in investment and operational models to take into account these issues.

As described in Section “Spatial representation and power flow”, NTCs take into account power system stability constraints. However, NTCs are calculated for specific generation portfolios and operating situations, and their applicability as stability indicators in investment planning is limited.

Capacity adequacy

Capacity adequacy means that there is a sufficient amount of generation capacity to cover the different load situations that can occur in the system, including the predicted peak load period. Capacity adequacy is usually evaluated using indices such as loss of load expectation (LOLE), which means the number of hours or days per year in which demand is expected not to be met. A related term is the value of lost load (VOLL), which represents the maximum electricity price that consumers are willing to pay to avoid an outage. Planning (reserve) margin and capacity (reserve) margin are terms used in power system planning to depict the fraction by which dependable supply capacity exceeds peak demand. They should not be confused with the operational reserves (primary, secondary and tertiary reserves) discussed in the previous subsections. Capacity value or capacity credit represents the proportion of the capacity that can be counted on at times of peak load, i.e., the ratio of dependable capacity to maximum or nameplate capacity.

The increasing share of VG and electricity market integration affects the calculation of capacity adequacy. In the calculation of planning reserve margin, dependable supply capacity can also include alternative sources of supply to generation, such as storage discharging, import, and demand response. Traditional methods to model available capacities are unable to properly represent the value of these alternative sources of supply. For wind power generation, the preferred capacity value calculation methodology is effective load carrying capability (ELCC) (Keane et al., 2011). A new resource like wind power will decrease the loss of load probability by the virtue of increased generation. In ELCC calculation, load is increased until the LOLE reaches the original level. ELCC is therefore the additional load the new resource is able to support without degrading the LOLE. It is typical that the capacity value of VG decreases when the installed capacity of VG increases. Although capacity value and LOLE cannot be directly calculated in traditional linear planning models, the results given by the models can be examined using these calculations.

In multi-region systems, practical methods are needed to tackle the difficulty to consider the value of transmission links (Thomasson & Söder, 2017). Moreover, storage discharging and different forms of demand response require methods that are more rigorous. Combining these aspects with models using representative periods further complicates the treatment of capacity adequacy in the planning problem. Selecting the representative periods and the planning margins becomes more difficult because the most constraining situations do not necessarily occur at the same time in every region.

Another question related to capacity adequacy is the revenue sufficiency of generators. Scarcity pricing and forward capacity markets have been proposed as two distinct directions in terms of market designs to ensure revenue sufficiency, while there are also developments to ensure sufficient flexible capacity (Ela et al., 2018). Taking these aspects into account can potentially have a large impact on investment optimization.

Energy system integration

Traditionally, ESOMs have taken into account interactions of energy sectors, whereas GEP models and UCED models have often only considered the power sector. However, high benefits can be achieved by increasing energy system flexibility through energy system integration, which means coupling of different energy sectors, such as electricity, heat, gas, transport, and industry. For example, studies have indicated that heat pumps, heat storages and electric boilers in district heating systems can significantly facilitate the integration of wind and solar power (Kiviluoma & Meibom, 2010), (Mathiesen & Lund, 2009).

Technology options in the investment models have long covered a range of conventional power plants, whereas more advanced technology options, such as different storage technologies may have been missing completely. Along with the energy system integration, it has become increasingly important to consider technological diversity in the models. This means that not only dedicated electricity storages need to be modelled, but also power-to-heat, power-to-gas and power-to-chemicals facilities as well as electric vehicles.

Energy system integration can also be seen in future demand and customer behaviour, which should be properly considered when evaluating the design and operation of future energy systems. Load profiles in traditional GEP models and UCED models have usually been exogenous and based on historical profiles, which is likely to misrepresent the future demand. It is expected that future electricity demand will be impacted by, e.g., energy efficiency, electric vehicles, residential heat pumps, smart metering with load controllability, and microgeneration (Boßmann & Staffell, 2015).

Long-term uncertainty

Power systems with large shares of VG are exposed to interannual variations in wind speed and solar radiation, in addition to other typical long-term uncertainties, including those in hydropower inflows, demand, fuel prices, CO_2 prices, investment costs, and operation and maintenance costs. Uncertainty related to some of these random variables can be handled using, e.g., Monte-Carlo methods, stochastic programming, or robust optimization. These methods have been applied to long-term energy system models (Messner, Golodnikov, & Gritsevskii, 1996), (Kanudia & Loulou, 1998), capacity expansion planning (Jin et al., 2014), (Dehghan, Amjady, & Kazemi, 2014) and operational optimization (Koltsaklis & Nazos, 2017).

Sometimes uncertainties are too complex to be directly represented in the models. On the other hand, in some cases the objective is to compare the impact of a few different policies or future visions on the optimal generation portfolio. In these cases, a set of deterministic scenarios is typically created. It is important to consider path dependency in the scenarios, because energy system investments tie up large amounts of capital and have long lifetimes. Decisions made today affect in decades to come. Some investment models are myopic, whereas others have longer horizons. The weakness of the myopic models with, for example, a one-year horizon is that they optimize the investments based on that year only and the generation portfolio is likely to be suboptimal in a longer timeframe. On the other hand, uncertainty increases with longer planning horizons and not considering that uncertainty will also lead to suboptimal solutions.

Moreover, typical expansion models assume that the decision maker has a neutral risk preference when in fact risk aversion in the investment decisions changes the results, as shown in (Baringo & Conejo, 2013), where the authors proposed a risk-constrained multi-stage stochastic programming model to make optimal investment decisions on wind power facilities using conditional value at risk as risk measure. They took into account eventual future decline in wind power investment costs, and the significant financial risk coming from plant operations. The issue of risk aversion in the long-term investment planning problem has also been considered in the Brazilian context (Bruno, Ahmed, Shapiro, & Street, 2016). The authors used a real options approach to model risk aversion towards VG power production, and compared the investment plans of risk neutral against risk averse attitudes.

MODELLING APPROACHES

Various modelling tools can be used to evaluate the design and operation of energy systems. In order to fully encompass all different challenges in planning and operating energy systems, there is a need for a variety of models that capture both the physical behaviour of energy systems as well as market mechanisms.

Overview of the proposed categorization

The model categorization proposed in our analysis is presented in Figure 4. Models are categorized into four different levels, in order of increasing complexity:

- The first level is divided into approaches using investment models only and operational models only.
- The second level consists of unidirectionally soft-linked investment and operational models.
- The third level contains iterative approaches: bidirectionally soft-linked investment and operational models, and iterative use of operational models together with an investment update loop.
- The fourth level represents co-optimized investments and operation.

The approaches are described in more detail in the following subsections.

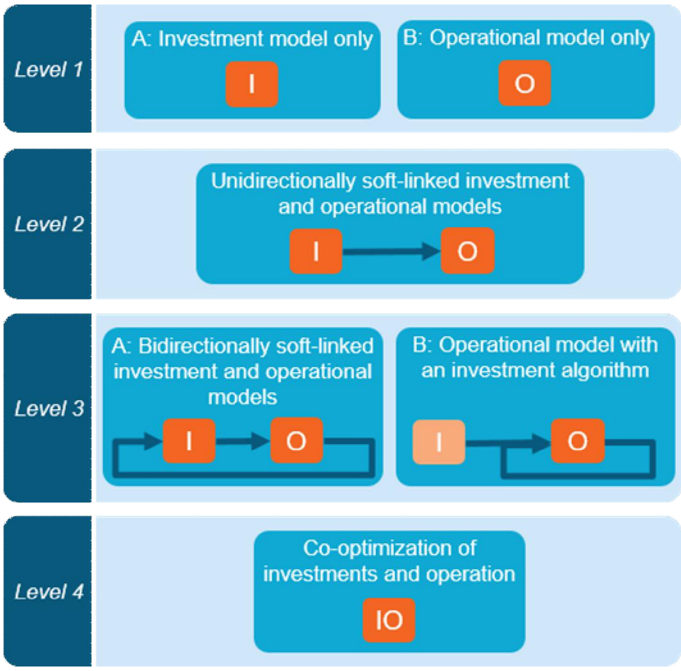


Figure 4 Classification of modelling approaches.

Level 1A: Investment model only

Long-term energy system optimization models (ESOMs), such as MARKAL/TIMES (Loulou, Remme, Kanudia, Lehtila, & Goldstein, 2005), MESSAGE (Schrattenholzer, 1981), and OSeMOSYS (Howells et al., 2011), are used to assess consistent pathways of energy systems and to evaluate public policies. These models typically consider several decades and take into account interactions of energy sectors. Consequently, the studies often use a coarse temporal resolution and may suffer from the lack of short-term chronology inside a year. Thus, many intertemporal operational constraints are not adequately considered when these models are used. The representation of power plants in ESOMs is technology based and the technical constraints of individual units are not normally considered.

Capacity expansion planning models are traditionally used to optimize power system investments, focusing either on generation or transmission capacity expansion, or both. Dedicated transmission expansion planning models are beyond the scope of this review. Examples of generation expansion planning (GEP) models are Balmorel (Ravn et al., 2001), LIMES-EU (Nahmmacher, Schmid, & Knopf, 2014), OptGEN (PSR, 2016), POWER (Frew, Becker, Dvorak, Andresen, & Jacobson, 2016), ReEDS (Short et al., 2011), REMix (Gils, Scholz, Pregger, Luca de Tena, & Heide, 2017), SWITCH (Fripp, 2012) and WASP (IAEA, 2001). GEP models incorporate some operational details but mainly consider investment possibilities and policy constraints such as annual carbon limits. These models typically represent their planning horizon using chronological time steps but with reduced time series, often by means of a set of representative periods. Some GEP models consider one year at each run (Zerrahn & Schill, 2015), some allow optimizing several decades year by year or using a rolling horizon (Ravn et al., 2001), and some solve multiple decades in a single optimization (Short et al., 2011). The models do not typically consider other energy sectors than the power sector, although some include, for example, the heat sector (Ravn et al., 2001).

Low temporal resolution and/or lack of operational constraints in traditional ESOMs and GEP models tend to result in overestimation of the role of VG and baseload power plants (Collins, Deane, Poncelet, et al., 2017; IRENA, 2017). On the other hand, when simplified constraints are introduced, they are typically unable to properly mimic the operational requirements arising from the variability and uncertainty of VG, and consequently they may overly restrict wind and solar deployment (Pietzcker et al., 2017). In addition, the selection of representative periods in GEP models has a strong impact on the planning outcome, which decreases the reliability of the results given by these models, as does the low spatial resolution in many of the traditional ESOMs and GEP models.

Level 1B: Operational model only

Short-term operational models (also referred to as production cost models or scheduling models) are used, among other purposes, for studies considering the operational impacts of VG on power systems. Examples of such models are FESTIV (Ela & O'Malley, 2012), LUSYM (Van den Bergh, Bruninx, Delarue, & D'haeseleer, 2015), SDDP (M. V. F. Pereira & Pinto, 1991) and WILMAR (Meibom et al., 2011). Short-term operational models are not designed to optimize investments; thus, they can only be used to explore exogenous generation capacity scenarios. On the other hand, operational models have a higher temporal resolution than investment models and they maintain the chronology between the time steps inside a year. The models often allow for a MILP-based representation of unit commitment and economic dispatch (UCED). Consequently, they allow for a detailed representation of load, conventional generation, wind power, solar power, hydropower and storage. Hence, it is possible to examine the operational restrictions and costs of thermal power plants as well as the evolution of storage state (Holttinen et al., 2013).

Operational models often consider one year using a rolling optimization horizon typically 24–48 hours long. An additional look-ahead period can be included in order to avoid issues with intertemporal constraints at the optimization horizon boundaries, and – if not using perfect forecasts – to capture the difference between optimization with forecasted wind/solar/load and more accurate dispatch closer to delivery hour (Deane, Chiodi, Gargiulo, & Ó Gallachóir, 2012), (Meibom et al., 2011). Just as GEP models, operational models often only consider the power sector. Scenarios are hand built and the asset structure may be far from optimal. As such, they have limited applicability and are not well suited for assessing the long-term optimality of the generation mix by themselves.

Level 2: Unidirectionally soft-linked investment and operational models

Recently, much effort has been made to combine the benefits of investment and operational models, and different approaches have been taken to tackle the complex problem of generation expansion planning under operational constraints. Some studies have focused on soft-linking methods, i.e., exchange of model outputs and inputs.

In unidirectional soft-linking approaches, the capacity expansion outcome of the investment model is given as input for the operational model. Although the outcomes of the two models may be compared and the capacity adequacy may be checked, no automated feedback is given from the operational model to the investment model to improve the results. The investment model in these approaches can be an ESOM or a GEP model.

Soft-linking methods are likely to result in suboptimal planning outcome and results with an unknown quantity of residual uncertainty. Given the nature of the information exchange between the models, these methods may tend to overestimate costs, when the investment costs are added to the operational costs of a suboptimal generation mix.

Level 3A: Bidirectionally soft-linked investment and operational models

A more advanced method to combine the benefits of investment models and operational models is to run the two models iteratively, ideally until convergence or global optimum is reached. Furthermore, although this paper focuses on planning models and operational models, the soft-linking methodology can be extended to more detailed grid models, as depicted in Figure 5.

However, it can be difficult to specify the feedback from the operational model to the investment model. Depending on the model objectives, it can be a change in parameters or constraints. Examples of the options for the procedure are:

- When there is a difference between the planning and operational model results, add an artificial variable cost to the investment options in the planning model and run the planning model again. (Kiviluoma, Rinne, & Helistö, 2017)
- Run a range of cases using the planning model, each having a different artificial variable cost in the investment options. Run the operational model with true variable costs for each of the cases. Sum fixed costs from the planning model and variable costs from the operational model and find the case with the lowest costs. (Kiviluoma et al., 2017)
- Solve the planning and operational problems separately in a built-in iterative procedure using Benders decomposition. Optimality cuts produced by the operational model are included in the planning problem at each iteration before performing the investment cost calculation. This method is already very close to co-optimization (level 4). (M. V. Pereira, 2016).

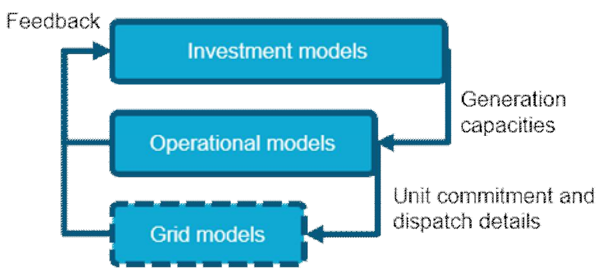


Figure 5 Examples of links between different energy system model types

Level 3B: Operational model with an investment algorithm

Another form of the iterative approach is to run only the operational model iteratively, as depicted in Figure 6. The first step also in this approach is to determine an initial set of investments. The second step is to run the operational model with the initial set of investments. Next, the investment set is updated based on, for example, revenue sufficiency (Lopez-Botet et al., 2014), where prices from the operational model indicate whether to build more plants or remove plants that do not have sufficient revenues. After updating the investment set, the operational model is run again. The iteration ends when convergence is reached.

This approach differs from the previous bidirectional method in the sense that there is no investment optimization model that would be run after the operational model. Instead, a separate algorithm is used to update the investment set. There are also other updating algorithms in addition to the one based on revenue sufficiency, and we will return to them in Section “Review findings: Comparison of modelling approaches”.

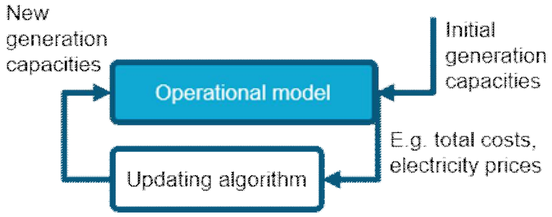


Figure 6 Running operational models iteratively

Level 4: Co-optimized investments and operation

The method that theoretically captures the highest level of complexity in generation planning under operational constraints is co-optimization of investments and operation. Using this method, it is, at least in theory, possible to include all relevant operational details in the planning problem. In practice, there is a trade-off between the accuracy of the temporal representation and the accuracy of the operational constraints in the models. Smaller systems are naturally more tractable than larger ones, and for them the increased complexity of the co-optimization method may not be an issue. However, for larger systems the approach can result in computational problems. Generally, the option to avoid larger systems becoming intractable is to loosen some constraints in the model or to reduce the temporal accuracy. Even if large computing clusters are available for the modeller, it is always possible to increase the level of detail in temporal, spatial and technological dimensions until the problem becomes too large. For example, including stochastic short-term forecasts in the long-term planning problem can create extremely large models. A desirable level of detail for a given modelling task can also be dictated by more practical concerns like data availability and data management problems.

It is not clear where the border between level 1A and level 4 is. When the operational detail of a model at level 1A is improved step by step, at some point it will turn into a level 4 model. Level 4 models should include all those operational details that have an important impact on the planning results, and the results from (B. Palmintier, 2014) can provide some guidance on this. The author found that removing maintenance constraints or operating reserve constraints from the planning problem causes a considerable increase in cost error. Omitting hourly ramping constraints did not appreciably increase the error, and omitting start-up costs and constraints or minimum uptime and downtime constraints also resulted in a rather small error. Given the importance of this question, future research should systematically corroborate those results with different models and in different systems.

REVIEW FINDINGS: COMPARISON OF MODELLING APPROACHES

This section compares the modelling approaches found in the literature of VG integration studies. The literature is reviewed in the same order as we presented the categorization in Section "Modelling approaches", .i.e., we start with the studies based on investment models only and we end with the studies using co-optimization. First, the characteristics of the studies are summarized in tables and in a node graph. Then, significant findings of the studies and the differences in the results based on the modelling approaches are discussed.

Overview of the selected studies

We collected to the review VG integration studies that reported their methodology in an adequate manner and tried to take into account both the planning and operation of power systems. We categorized the studies based on the categorization in Section "Modelling approaches", and when there was abundance of studies in some modelling approach category, we accepted only those studies that internally investigated the impact of operational detail in planning or otherwise proposed an interesting methodology for models in that category. The final selection includes 12 studies from level 1A, four studies from level 1B, 13 studies from level 2, three studies from level 3A, two studies from level 3B, and 13 studies from level 4. The selection is further elaborated in each of the following subsections. Table 1–Table 4 present the spatial and temporal characteristics of the selected VG integration studies, whereas other modelling features and details are presented in Table 5–Table 8.

Related to the selection and categorization of the studies, there are a few details and choices that need attention. Because of the ambiguous amount of required operational constraints, part of the studies presented in the level 4 are actually a mixture of level 1A and level 4. Similarly, some of the decomposition-based approaches in the level 4 could be categorized either as level 3A or as level 4. If the model had a detailed temporal and spatial resolution but the technical operational constraints were not detailed enough, it was categorized in the level 1A. This choice was also made when the approach combined a long-term planning model and a separate simplified dispatch model. Finally, some of the studies are based on a model developed specifically for the study in question, whereas others are based on more widely-used models. We have treated the application-specific models and widely-used models equally, analysing the characteristics and features used in each of the selected VG integration studies, i.e., we have not analysed what the full capabilities of the widely-used models are and how they could be applied to other case studies.

The tables show how the different modelling challenges described in Section "Modelling challenges" were tackled in the VG integration studies. Long-term uncertainty issues are not presented in the tables, as in general the selected VG integration studies did not explicitly consider those issues. Long-term uncertainty was mostly taken into account by examining separate scenarios. Furthermore, although the issue of capacity adequacy in the context of a high share of VG is widely discussed in academic circles (Conejo, Baringo Morales, Kazempour, & Siddiqui, 2016), to our knowledge such probabilistic measures to assess capacity adequacy are not widely used or taken into account in actual planning. However, some applications exist, such as the Monte-Carlo-based methods used by ENTSO-E (ENTSO-E, 2017).

Figure 7 shows an overall summary of the links between the modelling approaches (i.e. levels 1–4) and the ways to tackle the modelling challenges. The summary is constructed based on findings in Table 1–Table 8. Traditionally, ESOMs include multiple energy sectors, but the figure reveals that when temporal and technical detail of investment models (level 1A) is enhanced, there is a trade-off with sectoral coverage. Electricity sector was included in all studies and is not shown in the graph for clarity. Furthermore, the summary shows that while the selected studies based on operational model only (level 1B) and co-optimization (level 4) had high detail in temporal representation and unit operation, their grid representation was often highly simplified. By contrast, the selected studies based on unidirectionally linked models (level 2) had the highest level of detail in these three aspects in the operational stage – nevertheless, this does not necessarily make the approach the most accurate for planning. When interpreting the results, it should also be noted that the selection of studies based on bidirectionally linked models (level 3A) and operational models with an investment algorithm (level 3B) was very small.

Significant findings of the studies and the differences in the results are discussed in the following subsections.

Table 1 Spatial and temporal characteristics of studies at level 1 – one model only

Reference and model name	Temporal representation	Spatial representation
	1A: Investment models	
Kannan and Turton 2013: TIMES	Horizon 2000–2110, milestone year every 1–20 years, resolution 8-288 time slices	Switzerland as one region
Welsch et al. 2014: OSeMOSYS	Horizon 2010–2050, resolution 12 time slices	Ireland
Cole et al. 2016, Short et al. 2011: RWGTM and ReEDS	RWGTM: 2010–2070, every 1–5 years; ReEDS: 2010–2050, every 2 years, resolution 17 time slices	RWGTM: over 290 global natural gas demand regions; ReEDS: 356 resource regions and 134 balancing areas in US
Frew and Jacobson 2016, Frew et al. 2016: POWER	1-year horizon, 365 representative days with 2–8-h resolution or 8–168 representative days with 1-h resolution	3 extents: California, the western US, the contiguous US; 2 resolutions: uniform buildout, site-by-site buildout
De Jonghe et al. 2011	One year at hourly resolution	Time series from Denmark
Nahmmacher et al. 2016, Nahmmacher et al. 2014: LIMES-EU	Horizon 2010–2050, milestone year every 5 years, 1–100 representative days, 8 time slices per day	Europe as 29 regions
Scholz et al. 2017: REMix	Full year at hourly resolution	Europe as 15 regions
Mileva et al. 2016: SWITCH	Horizon to 2050 with decadal investment period. Investment optimization: 600 h; Dispatch verification: 8760 h.	50 "load zones" in the WECC
Gils and Simon 2017: Mesap-PlaNet and REMix	Mesap-PlaNet: horizon until 2050, 5-year steps; REMix: one full year (2050) at hourly resolution	Canary Islands as 9 regions
Pfenninger 2017: Calliope	1-year horizon, 144-8784 time steps, different reduction methods; also 25 years of time series, 10-100 selected days	Great Britain as 20 zones
Moore et al. 2018: TIMES and highRES	TIMES: 2010-2050, milestone year every 5 years; highRES: one year (2050) at hourly resolution	Great Britain as 20 load zones and 0.5° longitude and latitude grid squares for renewables
Pineda et al. 2016	1-year or 3-year horizon, 10 time segments	IEEE Reliability Test System
	1B: Operational models	
Shortt et al. 2013: FAST	One year at hourly resolution	3 cases: Finland, Ireland, Texas
Deane et al. 2014: PLEXOS	One year (2020) at 5–60-min resolution	Ireland (All Island as two regions)
O'Dwyer and Flynn 2015: PLEXOS	One year (2025) at 15–60-min resolution	Ireland

Troy et al. 2010: WILMAR	One year (2020) at hourly resolution	Ireland

Table 2 Spatial and temporal characteristics of studies at level 2 – unidirectional soft-linking

Reference and model name	Temporal representation	Spatial representation
Mai et al. 2012, Mai et al. 2014, Short et al. 2011: ReEDS and GridView	ReEDS: 2010–2050 with time slices; GridView: full year (2050) at hourly resolution	Continental US
Lew et al. 2013, Short et al. 2011: ReEDS and PLEXOS	ReEDS: time slices; PLEXOS: full year (2020) at 5-min resolution	Western Interconnection of the US
Deane et al. 2012: TIMES and PLEXOS	TIMES: horizon 2005–2050, resolution 12 time slices; PLEXOS: full year (2020) at 30-min resolution	Ireland
Deane et al. 2015: TIMES and PLEXOS	TIMES: horizon 2010–2040, resolution 12 time slices; PLEXOS: full year (2030) at hourly resolution	Italy (as 6 regions)
Poncelet et al. 2016: TIMES and LUSYM	TIMES: horizon 2014–2055 with five milestone years, resolution 12 time slices, different approaches to improve the representation; LUSYM: hourly resolution	Belgium
Brouwer et al. 2015: MARKAL and REPOWERS	MARKAL: horizon until 2050, milestone year every 5 years, resolution 9 time slices; REPOWERS: 2030 and 2050 at hourly resolution	The Netherlands
Collins, Deane and Ó Gallachóir 2017: PRIMES and PLEXOS	PRIMES: horizon until 2030(–2050); PLEXOS: full year (2030) at hourly resolution	EU-28 Member States
Gerbaulet and Lorenz 2017: dynELMOD	2015–2050 in five-year steps, 351 hours per year in the investment phase, 8760 hours per year in the dispatch phase	33 European countries
DNV GL et al. 2014: PLEXOS and DSIM	PLEXOS: 2020–2030(–2050) with reduced time series; DSIM: full year at hourly resolution	Europe (as 74 individual nodes in DSIM)
Chaudry et al. 2011: MARKAL and WASP and CGEN	MARKAL: horizon until 2050; WASP: load duration curve	UK
Kiviluoma et al. 2017: Balmorel and WILMAR	Balmorel: 1-year horizon (2050), 3 representative weeks at hourly resolution; WILMAR: full year at hourly resolution	North Europe as 14 regions
Ikäheimo et al. 2018: TIMES and Balmorel	TIMES: 2010–2050, milestone year every 10 years, 8 time slices per year; Balmorel: one full year at hourly resolution	TIMES: Nordic countries by country + East and West Europe; Balmorel: North Europe as 14 regions
Hart and Jacobson 2011	Planning model: 2-year horizon, 28 selected days at hourly resolution; Operational model: 2 years at hourly resolution	California as one region

Table 3 Spatial and temporal characteristics of studies at level 3 – iteration

Reference and model name	Temporal representation	Spatial representation
	3A: Bidirectional soft-linking	
Rosen 2008: PERSEUS and AEOLIUS	PERSEUS: horizon 2000–2020, characteristic year every five years, resolution 36 time slots per year; AEOLIUS: each characteristic year with 3 representative days per month and hourly resolution	PERSEUS: 21 European countries as 25 regions; AEOLIUS: Germany and Spain
Pina et al. 2013: TIMES and EnergyPLAN	TIMES: horizon 2005–2050, resolution 288 time slices; EnergyPLAN: full year at hourly resolution.	Portugal
Mills and Wiser 2012	One year (2030) at hourly resolution	California as one region

	3B: Operational model with an investment algorithm	
Belderbos and Delarue 2015	MILP GEP: 1-year horizon, 3 representative days at hourly resolution; UC: full year at hourly resolution	Time series from Belgium
Lopez-Botet et al. 2014: CONTINENTAL	Hourly resolution	Europe

Table 4 Spatial and temporal characteristics of studies at level 4 – co-optimization

Reference and model name	Temporal representation	Spatial representation
Ma et al. 2013: UCC algorithm	1-year horizon, 5 representative weeks at hourly resolution	IEEE Reliability Test System
Palmintier and Webster 2016: MEPO	One year (2035) at hourly resolution	Texas
Jin et al. 2014	1-year horizon, 3 representative weeks at hourly resolution, 3 wind profiles for each week	Illinois as one region
Levin and Botterud 2015	1-year horizon, 3 representative weeks at hourly resolution, 3 wind profiles for each week	Illinois as one region
Brijs et al. 2017	One year at hourly resolution	Time series from Belgium
Koltsaklis and Georgiadis 2015	Horizon 2014–2030, 12 representative days each year at hourly resolution	Greece (2 regions with NTC limit in between, 5 zones for renewables)
Pereira et al. 2017	10-year horizon, 4 representative days each year at hourly resolution	Portugal
Nicolosi et al. 2010: THEA	Horizon 2008–2030(–2070), milestone year every 5 years, resolution 16–8760 time slices	Texas (with price zones separately)
Florez-Quiroz et al. 2016	Horizon 2012–2030, 13 typical weeks each year at hourly resolution	Chilean Northern Interconnected System as one region
Mai et al. 2013: RPM	2010–2030, every 5 years, hourly resolution for each year	Colorado, with 27 internal zones and 4 external zones
Pudjianto et al. 2014	One year (2030) at hourly resolution	GB as 4 regions and with links to Ireland and Continental Europe
Ramírez et al. 2016	1-year horizon, 5 representative weeks at hourly resolution	UK
de Sisternes 2014, de Sisternes et al. 2015: IMRES	1-year horizon, four representative weeks at hourly resolution	Greenfield system with 77 GW peak load and historical VG profiles

Table 5 Modelling features and details of studies at level 1 – one model only

	Unit operation		Transmission			Balancing and stability			Capacity adequacy			Sectors			Mathematical framework		
Reference and model name	**UC (including type)**	**Stylized UC constraints**	**DC power flow**	**Power transport**	**Copper plate**	**Balancing market**	**Operating reserves**	**Special constraints**	**Separate capacity adequacy constraint**	**Alternative supply sources considered**	**LOLE calculation or similar**	**Electricity**	**Heat**	**Natural gas**	**LP**	**MILP**	**Other**
1A: Investment models																	
Kannan and Turton 2013: TIMES	–	–	–	–	Y, EX	–	–	–	–	–	–	Y	–	–	Y	–	–
Welsch et al. 2014: OSeMOSYS	–	MSG	–	–	–	–	Y	NS	Y	–	–	Y	–	–	Y	–	–
Cole et al. 2016, Short et al. 2011: RWGTM and ReEDS	–	–	–	Y	–	–	–	–	Y	Y	–	Y	–	Y	Y	–	–
Frew and Jacobson 2016, Frew et al. 2016: POWER	–	MSG	–	Y	–	–	Y	–	–	–	–	Y	–	–	Y	–	–
De Jonghe et al. 2011	–	MSG	–	–	Y, EX	–	Y	–	–	–	–	Y	–	–	Y	–	–
Nahmmacher et al. 2016, Nahmmacher et al. 2014: LIMES-EU	–	MSG	–	Y	–	–	–	–	–	–	–	Y	–	–	Y	–	–
Scholz et al. 2017: REMix	–	–	–	Y	–	–	–	–	–	–	–	Y	Y	–	Y	–	–
Mileva et al. 2016: SWITCH	–	–	–	Y	–	–	–	–	Y	Y	–	Y	–	–	Y	–	–
Gils and Simon 2017: Mesap-PlaNet and REMix	–	–	–	Y	–	–	–	–	–	–	–	Y	Y	S	Y	–	–
Pfenninger 2017: Calliope	–	–	–	Y	–	–	–	–	–	–	–	Y	–	–	Y	–	–
Moore et al 2018: TIMES and highRES	–	–	–	Y	–	–	–	–	–	–	–	Y	–	–	Y	–	–
Pineda et al. 2016	–	–	Y	–	–	Y	–	–	–	–	–	Y	–	–	–	Y	–
1B: Operational models																	
Shortt et al. 2013: FAST	B	–	–	–	Y	–	Y	–	Y	–	–	Y	–	–	–	–	H
Deane et al. 2014: PLEXOS	B	–	–	Y	–	–	Y	–	–	–	–	Y	–	–	–	Y	–
O’Dwyer and Flynn 2015: PLEXOS	B	–	–	–	Y, EX	–	Y	–	–	–	–	Y	–	–	–	Y	–
Troy et al. 2010: WILMAR	I	–	–	–	Y, EX	Y	Y	ON	Y	Y	–	Y	–	–	–	Y	–

Y: yes
–: not included or no information found
B: binary
I: integer
MSG: minimum stable generation levels
EX: exchange considered
NS: non-synchronous limit
ON: minimum number of online units
S: synthetic hydrocarbons/hydrogen
H: heuristics

Table 6 Modelling features and details of studies at level 2 – unidirectional soft-linking

	Unit operation		Transmission			Balancing and stability			Capacity adequacy			Sectors			Mathematical framework		
Reference and model name	**UC (including type)**	**Stylized UC constraints**	**DC power flow**	**Power transport**	**Copper plate**	**Balancing market**	**Operating reserves**	**Special constraints**	**Separate capacity adequacy constraint**	**Alternative supply sources considered**	**LOLE calculation or similar**	**Electricity**	**Heat**	**Natural gas**	**LP**	**MILP**	**Other**
Mai et al. 2012, Mai et al. 2014, Short et al. 2011: ReEDS and GridView	Y	–	Y	–	–	–	Y	–	Y	Y	–	Y	–	–	Y	–	–
Lew et al. 2013, Short et al. 2011: ReEDS and PLEXOS	Y	–	Y	–	–	–	Y	–	Y	Y	–	Y	–	–	Y	Y	–
Deane et al. 2012: TIMES and PLEXOS	B	–	–	–	–	–	Y	NS	–	–	Y	Y	–	–	Y	Y	–
Deane et al. 2015: TIMES and PLEXOS	B	–	Y	–	–	–	Y	–	–	–	Y	Y	–	–	Y	Y	–
Poncelet et al. 2016: TIMES and LUSYM	B	–	–	–	Y	–	–	–	Y	–	–	Y	–	–	Y	Y	–
Brouwer et al. 2015: MARKAL and REPOWERS	Y	–	–	–	EX	–	Y	–	–	–	–	Y	Y	–	Y	–	LR
Collins, Deane and Ó Gallachóir 2017: PRIMES and PLEXOS	RR	–	–	Y	–	–	–	IN	–	–	–	Y	–	–	–	–	–
Gerbaulet and Lorenz 2017: dynELMOD	–	RC	Y	Y	–	–	–	–	–	–	–	Y	–	–	Y	–	–
DNV GL et al. 2014: PLEXOS and DSIM	Y	–	Y	–	–	Y	Y	–	Y	–	Y	Y	Y	–	–	–	–
Chaudry et al. 2011: MARKAL and WASP and CGEN	–	MSG	Y	–	–	–	–	–	Y	–	Y	Y	–	Y	Y	Y	NLP
Kiviluoma et al. 2017: Balmorel and WILMAR	R&I	–	–	Y	–	Y	Y	–	Y	(Y)	–	Y	Y	–	Y	Y	–
Ikäheimo et al. 2018: TIMES and Balmorel	R	–	–	Y	–	–	–	–	Y	(Y)	–	Y	Y	Y, S	Y	–	–
Hart and Jacobson 2011	–	NLF	–	–	Y	Y	–	–	–	–	Y	Y	–	–	Y	–	MC

Y: yes
–: not included or no information found
B: binary
RR: rounded relaxation
R&I: relaxed and integer variables compared
R: continuously relaxed
RC: ramping cost to take into account start-ups
MSG: minimum stable generation levels
NLF: no-load fuel consumption
EX: exchange considered
NS: non-synchronous limit
IN: inertia limit
(Y): limited consideration
S: synthetic hydrocarbons/hydrogen
LR: Lagrangian relaxation
NLP: nonlinear programming
MC: Monte Carlo

Table 7 Modelling features and details of studies at level 3 – iteration

	Unit operation		Transmission			Balancing and stability			Capacity adequacy			Sectors			Mathematical framework		
Reference and model name	**UC (including type)**	**Stylized UC constraints**	**DC power flow**	**Power transport**	**Copper plate**	**Balancing market**	**Operating reserves**	**Special constraints**	**Separate capacity adequacy constraint**	**Alternative supply sources considered**	**LOLE calculation or similar**	**Electricity**	**Heat**	**Natural gas**	**LP**	**MILP**	**Other**
3A: Bidirectional soft-linking																	
Rosen 2008: PERSEUS and AEOLIUS	Y	–	–	Y	–	Y	Y	–	Y	–	–	Y	Y	–	Y	–	H
Pina et al. 2013: TIMES and EnergyPLAN	Y	–	–	–	–	–	–	–	–	–	–	Y	–	–	Y	–	–
Mills and Wiser 2012	R	–	–	–	Y	Y	Y	–	–	–	–	Y	–	–	Y	–	–
3B: Operational model with an investment algorithm																	
Belderbos and Delarue 2015	B	–	–	–	Y	–	Y	–	–	–	–	Y	–	–	–	Y	–
Lopez-Botet et al. 2014: CONTINENTAL	I	–	–	Y	–	–	Y	–	Y	–	–	Y	–	–	–	–	H

Y: yes
–: not included or no information found
B: binary
I: integer
H: heuristics

Table 8 Modelling features and details of studies at level 4 – co-optimization

	Unit operation		Transmission			Balancing and stability			Capacity adequacy			Sectors			Mathematical framework		
Reference and model name	**UC (including type)**	**Stylized UC constraints**	**DC power flow**	**Power transport**	**Copper plate**	**Balancing market**	**Operating reserves**	**Special constraints**	**Separate capacity adequacy constraint**	**Alternative supply sources considered**	**LOLE calculation or similar**	**Electricity**	**Heat**	**Natural gas**	**LP**	**MILP**	**Other**
Ma et al. 2013: UCC algorithm	B	–	–	–	Y	–	Y	–	–	–	–	Y	–	–	–	Y	–
Palmintier and Webster 2016: MEPO	I	–	–	–	Y	–	Y	–	Y	–	–	Y	–	–	–	Y	–
Jin et al. 2014	B	–	–	–	Y	–	Y	–	–	–	–	Y	–	–	–	Y	–
Levin and Botterud 2015	I	–	–	–	Y	–	Y	–	–	–	–	Y	–	–	–	Y	–
Brijs et al. 2017	R	–	–	–	Y	–	Y	–	–	–	–	Y	–	–	Y	–	–
Koltsaklis and Georgiadis 2015	B	–	–	Y	–	–	Y	–	Y	Y	–	Y	–	–	–	Y	–
Pereira et al. 2017	–	QCF	–	–	Y	–	Y	–	Y	Y	–	Y	–	–	–	–	MINLP
Nicolosi et al. 2010: THEA	R	–	–	Y	–	–	Y	–	–	–	–	Y	–	–	Y	–	D
Florez-Quiroz et al. 2016	I	–	–	–	Y	–	Y	–	Y	–	–	Y	–	–	–	Y	D
Mai et al. 2013: RPM	B	–	–	Y	–	–	Y	–	Y	Y	–	Y	–	–	–	Y	–
Pudjianto et al. 2014	I	–	Y	–	–	–	Y	–	–	–	Y	Y	–	–	–	Y	–
Ramírez et al. 2016	I	–	–	–	Y	–	Y	–	–	–	–	Y	–	–	–	Y	–
de Sisternes 2014, de Sisternes et al. 2015: IMRES	B	–	–	–	–	–	–	–	–	–	–	Y	–	–	–	Y	–

Y: yes
–: not included or no information found
B: binary
I: integer
R: continuously relaxed
QCF: quadratic cost functions
MINLP: mixed integer nonlinear programming
D: decomposition

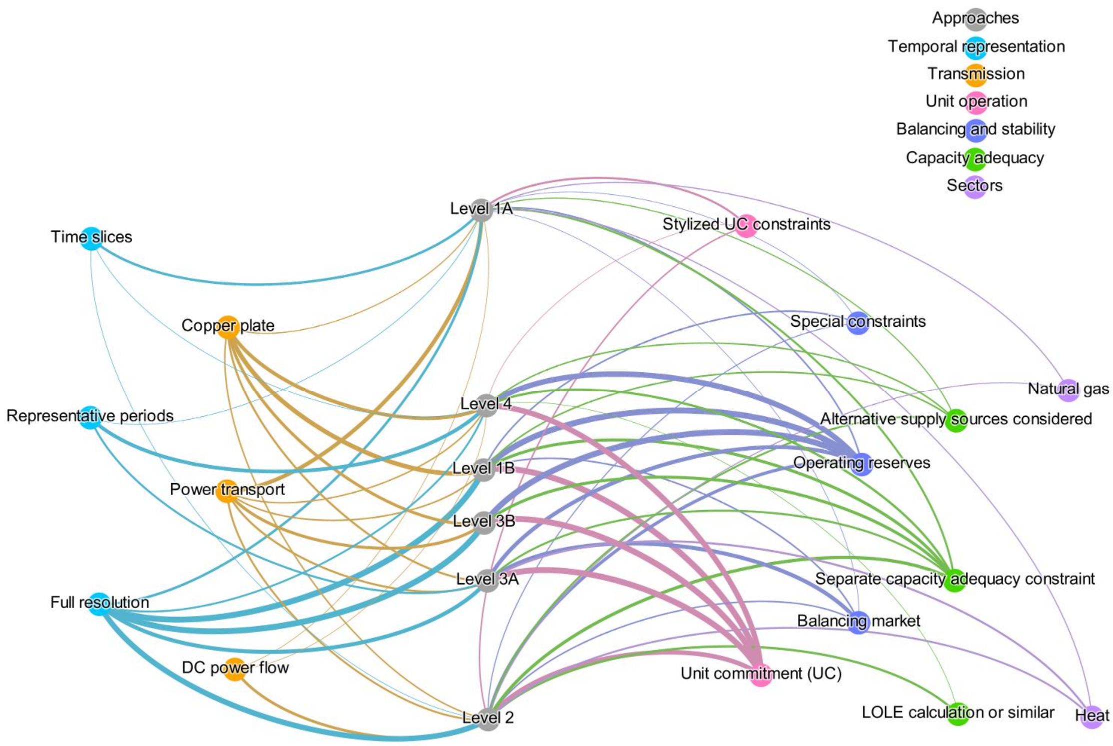


Figure 7 Connections between modelling approaches and methods to tackle modelling challenges. The thicker the connection, the higher the percentage of studies that utilized the tackling method in the respective modelling approach category.

Level 1A: Operational constraints in investment models

In recent years, efforts have been made to take into account short-term power system aspects in investment models. We selected 12 studies for the comparison (see Table 1 and Table 5).

Comparison of modelling approaches

Some of the 12 studies improved traditional investment model approaches by enhanced temporal representation (De Jonghe et al., 2011; Frew & Jacobson, 2016; Gils & Simon, 2017; Kannan & Turton, 2013; Mileva, Johnston, Nelson, & Kammen, 2016; Moore, Price, & Zeyringer, 2018; Pfenninger, 2017; Scholz, Gils, & Pietzcker, 2017) and some by additional operational constraints (De Jonghe et al., 2011; Frew & Jacobson, 2016; Nahmmacher, Schmid, Hirth, & Knopf, 2016; Welsch et al., 2014). The studies were based on times slices, representative periods, and full hourly resolution. The time horizon in the studies varied from one year to a century. Not all years in the horizon are necessarily considered individually – instead, the horizon is often divided into multi-year periods, each represented by a milestone year. The system is assumed to stay constant in all years within the same period or the system is assumed to evolve linearly between the milestone years.

Proper unit commitment was not considered in any of the studies, but some unit-related constraints such as minimum stable generation levels were included in part of the studies. The SWITCH model in (Mileva et al., 2016) included two phases: an investment optimization phase with 600 hours and a later dispatch verification phase with 8760 hours for the full year, but it is categorized here in level 1A instead of level 2 since the dispatch phase did not consider unit commitment. The Mesap-PlaNet and REMix models in (Gils & Simon, 2017) were combined through an iterative framework, but as with the SWITCH model, unit constraints were not considered in detail. Because of the same reason, the study combining a TIMES model and a highRES model falls into level 1A (Moore et al., 2018).

Capacity adequacy was considered differently in the selected studies: some included a planning reserve margin or a minimum capacity requirement, whereas others relied on load balance constraint. Stochastic programming or other special programming methods were not used to consider long-term uncertainty in any of the studies, and short-term uncertainty was considered through stochastic programming only in one of the studies (Pineda, Morales, & Boomsma, 2016).

Impact of temporal and operational details

The studies showed that selecting a higher temporal resolution and including more operational constraints affects the planning outcome. For example, Kannan and Turton (2013) observed that models with low temporal resolution tend to overestimate the potential of large baseload power plants and underestimate the need for flexibility provided, e.g., by peaking power plants and storage. The model in (Kannan & Turton, 2013) included 4 seasonal, 3 daily and 24 hourly time slices (288 in total) and it was compared to a model with only 8 time slices. The authors highlighted that the appropriate number of time slices depends on energy system characteristics, the research question to be answered, and the availability of data at the time slice level. The impact of temporal representation was also studied in (Nahmmacher et al., 2016), where the authors observed that a very low temporal resolution overestimates the share of VG in the electricity system and that already 48 time slices are sufficient to obtain model results that are very similar to those obtained with 800 time slices. Improving the temporal detail further from 288 or 800 time slices was not considered in (Kannan & Turton, 2013) and (Nahmmacher et al., 2016).

Different methods exist to reduce the temporal resolution of a planning model. According to the results of (Pfenninger, 2017), the best method depends on input data and the setup of model constraints. Furthermore, the same study concluded that planning model results with high shares of wind power and PV are likely unreliable if the model time series were based on only a single or few years of data. The unreliability arises from disregarding the interannual variability in wind power and PV generation.

While Kannan and Turton (2013) observed that a higher temporal resolution shows a reduced need for inflexible generation capacity, a similar finding was achieved by De Jonghe et al. (2011), but in their case the reduction in the need for inflexible generation capacity was due to the inclusion of additional operational constraints. It should be noted that this finding of increased flexibility need was made although the models in (Kannan & Turton, 2013) and (De Jonghe et al., 2011) were not able to properly consider unit commitment constraints of thermal power plants.

The impact of operational detail was also explored in (Welsch et al., 2014), where additional constraints were introduced to the energy system model OSeMOSYS. More specifically, the extended version of OSeMOSYS was able to capture minimum stable generation levels and operating reserve requirements. In addition, the extended model considered the maximum instantaneous share of wind more accurately than a simple OSeMOSYS model. However, the model neglected start-up costs and unit commitment optimization. In addition, the number of time slices was only 12 in the extended OSeMOSYS, which means that the yearly temporal resolution was over 700 times higher in the combined TIMES-PLEXOS that was used as a reference method. Nevertheless, when adding these operational details to OSeMOSYS, the annual generation in 2020 approached the results of the combined TIMES-PLEXOS (21.4% mismatch with the simple OSeMOSYS, and 5.0% mismatch with the extended OSeMOSYS). When the analysis was extended to 2050, with more freedom to choose the technology mix, the simple OSeMOSYS model assigned up to 23.5% of the total capacity to different power plant types compared to the enhanced model, resulting in 14.3% lower discounted costs in 2050. The authors highlighted that omitting the variability of renewables may underestimate the overall energy system costs and therefore the costs for meeting climate change or energy security targets.

It can be concluded based on these studies that models with a low temporal resolution or without important operational constraints tend to overestimate the value of inflexible power plants and underestimate the need for flexibility. In addition, models neglecting operational constraints significantly underestimate the overall costs when investigating systems with high VG shares. A significant finding is also that temporal representation based on only one year of time series is not sufficient, as there can be highly influential variations between the years. The best approach might be to find and combine enough representative periods from a much longer period of data assuming that running several years is not computationally possible.

Impact of temporal and spatial representations

Varying the temporal representation was also found to produce clear cost differences, which depend highly on the spatial representation. Frew and Jacobson (2016) quantified the impacts of the following adjustments: 365 representative days with a 2–8-hour resolution, and 8–168 representative days with a 1-hour resolution. The authors considered two spatial resolutions of site-by-site versus uniform fractional buildout across all solar and wind sites, and multiple spatial extents and aggregations, ranging from California to the western United States and the contiguous United States. The reduction of representative days from 168 to 56 produced a cost difference of only 1% for California. Reducing representative days from 56 to 8 produced a significantly larger difference for the western United States (19%) than for California (7%). An interesting observation was that reducing representative days actually increased the costs as the number of random “typical” days was decreased and extreme days had disproportionally more effect. The authors found the ideal representative day subset size to be 56 days for California and 28 days for the western United States, in terms of accuracy, computational requirements, and system configuration and operation.

Frew and Jacobson (2016) also explored the trade-offs of temporal and spatial resolution in the Californian case: reducing the resolution from 2 to 8 hours produced a cost difference of 2–5% when site-by-site spatial resolution was considered, and considering uniform buildout instead of the site-by-site resolution resulted in a difference of 3–8% with a 2-hour resolution. The differences were larger for a higher renewables target and smaller for a lower renewables target. Moreover, the authors highlighted the impact of geographic aggregation (i.e., optimizing a large spatial extent instead summing the results of optimizing individual regions), which produced a large cost reduction of 14% and 42% for the western and contiguous United States, respectively.

The importance of regional detail was also demonstrated by Cole, Medlock, and Jani (2016) in a work evaluating future renewable energy sources and natural gas interactions. Integrating the Rice World Gas Trade Model (RWGTM) and the Regional Energy Deployment System (ReEDS) model accounted for the increased use of natural gas for power system operations in the presence of VG as well as price changes due to increased consumption. A highly disaggregated regional representation in the models led to substantially different regional results compared to using a coarser representation of natural gas prices. Spatial detail can provide deeper insight into the benefits of different types of offshore wind power technologies as well, as indicated by a British case study that emphasized spatial diversification of renewables. At high renewable shares and low floating turbine cost assumptions, floating wind turbines were installed in order to get access to new renewable resources. Different levels of spatial detail were not compared: the study invariably managed renewables in 0.5° longitude and latitude grid cells.

The results highlight that models considering too few representative days may considerably overestimate the system costs if extreme days are over-represented, and that considering geographic aggregation can significantly affect the model outcomes. However, it can be argued that if extreme days are over-represented, then representative days have not been chosen as truly representative. The importance of spatial representation probably varies considerably depending on the modelling task. It could be valuable to have more studies that focus on this question.

Impact of forecast errors

It was also found that considering forecast errors in the planning phase can significantly affect the model outcome. The generation and transmission expansion planning framework introduced in (Pineda et al., 2016) included stochastic generation forecasts and considered both a day-ahead market and a balancing market. In addition to examining the impact of forecast errors on the planning outcome, two market designs were compared – differing in how efficiently they handled the forecast errors. The framework was applied to the IEEE Reliability Test System using a 1-year and a 3-year horizon with 10 time segments. The small size of the test system likely facilitated the application of the method. Omitting forecast errors in the planning phase led to suboptimal planning outcomes, while the efficiency of the market affected the way the planning outcome was suboptimal: with an efficient market the pre-defined renewable target was not met, and with an inefficient market the total system cost was significantly higher than the optimal one. It was also shown that a market design that efficiently handles forecast errors requires lower capacity expansion efforts to integrate a given amount of renewable production into a power system, as well as results in smaller system costs. Understanding the full impact of short-term uncertainty in long-term planning decisions is probably an interesting area for future research.

Need for storage and other flexibility options

Besides investigating the impacts of different modelling characteristics, investment models were used to provide insight into the need for storage and other flexibility options in future energy systems. The results of the SWITCH model showed storage deployment requirements in the multi-GW scale in most scenarios of high share of low cost solar power by 2040 and 2050, thus playing a central role in the Western Electricity Coordinating Council (WECC) power system (Mileva et al., 2016). Likewise, the results of the REMix model with full hourly resolution showed that the benefit of short-term electricity storage technologies increases with the solar share, whereas power transmission is particularly important with high wind shares (Scholz et al., 2017). In the REMix scenarios, hydrogen storage became economical at a high CO_2 price and especially at high wind shares. Gils and Simon (2017) highlighted the importance of storage, transmission and flexible demand in renewable energy supply systems for archipelagos. Furthermore, the results underlined the potential of linking power, heating and transport sectors as well as water supply for the integration of VG. Studies that aim to be policy relevant should consider sectoral links in futures with high shares of VG.

Level 1B: Investment planning using operational models

Pure operational models have a limited applicability in generation planning, but we have collected four studies based on operational modelling in this section to explore the insights that they can give to the required level of operational detail needed in planning (see Table 1 and Table 5).

Comparison of modelling methods and purposes

All the case studies considered one year of operation at a resolution of one hour or higher. In addition, they included detailed unit commitment optimization, either using binary variables or technology-clustered integer variables. The operational model was used for planning purposes in (Shortt, Kiviluoma, & O'Malley, 2013) only, while the other three studies focused on operational impacts. However, also the studies focusing on operational impacts have used different methods to add and remove flexibility options from the case study systems, and through the operational results, they can also provide insight into the constraints that may be influential in planning.

Short-term uncertainty and power system stability were taken into account differently in the selected studies. Stochastic forecasts and an intraday market were included in (Troy, Denny, & O'Malley, 2010), whereas the other three studies used perfect forecasts for hourly data. The studies also included various types of reserve requirements and stability constraints.

Impact of unit commitment constraints

The observations by Shortt et al. (2013) highlight the need to consider unit commitment constraints in generation expansion planning models when the share of VG increases. The authors found that the relative performance of a dispatch model in comparison to a unit commitment model is highly system specific but generally degrades with increasing variability. The unit commitment model was able to capture the chronological behaviour of units, including start-ups and shutdowns, while the dispatch model neglected the start-stop behaviour. Three test systems were used in the study: the Finnish and Irish power systems and ERCOT in Texas. The methodology was based on running the operational model with different technology mixes, specifically 17 886 cases (271 generation portfolios, and scenarios consisting of 2 cost-sets, 11 levels of installed wind and 3 test systems), and finding the least-cost portfolios for each scenario. The results showed that the generation cost error of the dispatch model increased from 3%–7% to 10%–16% when increasing the share of wind from 0% to 40%. In the highest wind case, introducing unit commitment constraints resulted in combined cycle gas turbines (CCGTs) being replaced by coal power plants, when assuming relatively low coal production costs. Assuming relatively high coal production costs, CCGT investments were expectedly replaced by open cycle gas turbine (OCGT) investments for the cases of Texas and Ireland, when introducing unit commitment constraints. For Finland, however, the impact was the opposite, which was explained by the spinning reserve needs. The results highlight the importance of including start-up costs at least when there are units with substantial start-up costs.

Impact of sub-hourly resolution and storage

The studies indicate that while sub-hourly modelling provides more accurate insight into the cycling of units, hourly or 30-min simulations appear to be adequate when system costs are solely of interest. The results of (Deane, Drayton, & Ó Gallachóir, 2014) showed that sub-hourly resolution captures more variability in system load and renewable generation, and is necessary to capture the inflexibilities of thermal units. However, the cost results of 5-min simulation were only approximately 1% higher than hourly simulation results. Likewise, the authors in (O'Dwyer & Flynn, 2015) concluded that sub-hourly UCED analysis is important for systems with very high wind shares, as hourly analysis underestimates the levels of conventional plant cycling. They observed that energy storage can reduce cycling and improve the efficiency of the system as a whole, with significant operating cost savings. However, the level of storage plant cycling required in order to minimize system costs, and the potential cost savings which can be generated, were underestimated by the hourly analysis, which was able to capture 90% of the operating cost reductions of storage, in comparison to 15-min simulation. The generation portfolios in (Deane et al., 2014) and (O'Dwyer & Flynn, 2015) were based on TSO publications. In (O'Dwyer & Flynn, 2015), some additional plant retirements were assumed and different storage plants were added to the system in turn.

The impact of storage on cycling was also analysed in (Troy et al., 2010), where storage actually exacerbated the cycling of thermal units for lower wind shares (<32%...42%). The impact of storage was explored by replacing the initial storage of 292 MW in the system with three 97.5-MW OCGTs. The paper examined the operation of thermal units in several scenarios with increasing shares of wind power. The generation portfolios in these wind power scenarios were based on a previous study. The results showed that baseload units are impacted differently by increasing levels of wind. CCGTs saw rapid increases in start-stop cycling and a plummeting capacity factor. On the other hand, coal units saw increased part-load operation and ramping, which was explained by the fact that they were the main thermal providers of primary reserve on the test system.

The studies presented two methods to consider the impacts of storage. Troy et al. (2010) used a method where the initial storage in the system was replaced by OCGTs with the same capacity, whereas O'Dwyer and Flynn (2015) added different storage plants to the system in turn in order to identify the storage characteristics that are important to systems with high VG shares. The different approaches in adding flexibility options to the operational analysis highlight the need for practices which ensure that the generation portfolio is not only adequate but also cost-effective.

Impact of system size

Ireland was used as a case study in all of the four studies. In (Shortt et al., 2013), case studies for Finland and Texas were also presented. Thus, all the studies considered a special case of a rather small synchronous system without explicit consideration of power grids. In (Deane et al., 2014), the Irish power system (All Island) was modelled as two regions, and (O'Dwyer & Flynn, 2015) and (Troy et al., 2010) took into account power exchange with neighbouring regions, but the studies were unable to capture the various impacts of transmission links in large interconnected systems. In (Troy et al., 2010), the impact of transmission interconnection on cycling was considered in the same way as the impact of storage, but as the interest was only in one 1000-MW interconnection of the small net-importer test system, the results cannot be generalized. In the case study, interconnection displaced generation from domestic units, resulting in increased cycling of baseload units compared to a system without interconnection.

The impact of system size may also be related to the need for sub-hourly resolution in the modelling. It is likely that the need for sub-hourly modelling is driven by the share of VG in the system, the geographical size of the system, and the number of units in the system, as VG increases flexibility needs while the large geographical size of the system and a large number of units can provide flexibility. However, the verification of this requires further studies.

Level 2: Unidirectional soft-linking

The literature considering unidirectionally soft-linked investment and operational models is wide. We selected 13 VG integration studies for the comparison in this category (see Table 2 and Table 6).

Comparison of temporal and operational details

The studies had different approaches for the temporal representation in the investment phase. Many studies considered a time horizon of several decades using time slices, whereas one of the studies used representative weeks and a one-year horizon (Kiviluoma, Rinne and Helistö, 2017). Hart and Jacobson (2011) selected 28 days over time series spanning two years. The operational model was typically run for a full year at hourly resolution. The dynELMOD model provides an alternative where the time horizon in the investment phase covers several decades at a resolution of 351 hours per year and the dispatch phase considers all 8760 hours of a year (Gerbaulet & Lorenz, 2017). Interestingly, while PLEXOS was used as the operational model with full hourly or sub-hourly resolution in (Lew et al., 2013), (Deane et al., 2012), (Deane, Gracceva, Chiodi, Gargiulo, & Gallachóir, 2015) and (Collins, Deane, & Ó Gallachóir, 2017), the role of PLEXOS was to provide the generation expansion planning results based on reduced time series in (DNV GL, Imperial College, & NERA Economic Consulting, 2014).

Unit commitment was not modelled in the investment phase in the integration studies in this section. In the operational phase, there were different approaches: Some models used binary unit commitment, integer unit commitment, or rounded relaxation of unit commitment. Minimum load limits of power plants were taken into account in (Chaudry et al., 2011), while the dynELMOD model (Gerbaulet & Lorenz, 2017) is based on linear programming without unit commitment. However, dynELMOD includes ramping costs to represent wear and tear of the power plant materials as well as additional fuel consumption due to ramping, and the assumed costs for ramping are slightly higher compared to a unit commitment model to account for the lack of binary and integer variables in dynELMOD. Although the original Balmorel model does not consider power plant start-ups, such variables were added to the model in (Ikäheimo, Pursiheimo, Kiviluoma, & Holttinen, 2018). The variables were continuously relaxed to keep the model linear. The model in (Hart & Jacobson, 2011) approximated the amount of online units and the corresponding no-load fuel consumption, but did not take into account start-ups.

Impact of temporal and operational representations

The authors in (Poncelet et al., 2016) proposed different approaches to improve the temporal representation in TIMES. They found that using a different approach of defining the time slices to explicitly account for VG variability leads to a higher accuracy than can be obtained by simply increasing the temporal resolution, while requiring a lower number of time slices. An even higher accuracy was achieved with a temporal representation based on selecting a set of representative days, albeit requiring a higher number of time slices. The benefit of using representative days is also that chronology is retained inside a day.

Furthermore, the effect of adding binary or integer unit commitment variables into an operational model has been found to be less significant than improving the temporal representation by considering full hourly resolution instead of a few representative weeks or a dozen of time slices (Kiviluoma et al., 2017), (Poncelet et al., 2016). In order to analyse this impact of operational detail separately from the temporal detail, the operational model was run with and without detailed operational constraints in (Poncelet et al., 2016) and (Kiviluoma et al., 2017). Poncelet et al. (2016) observed that the impact of temporal detail on the generation results is higher than the impact of operational detail, at least for high VG shares. The high temporal resolution of their simplified UCED model reduced the generation from nuclear and wind in the 2050 results, and increased the generation from OCGTs and CCGTs, compared to the results of the TIMES model they used for planning. Adding operational details to the UCED model further reduced wind generation and increased OCGT generation, but the impact was not as significant. The impact of increased temporal and operational detail on CCGTs was different in (Brouwer, van den Broek, Seebregts, & Faaij, 2015), where the authors observed that, compared to the MARKAL model results, natural gas combined cycle power production was reduced by 50–80%, as it was replaced by imports of cheaper, baseload power from abroad in the REPOWERS model. These differences can be due to the specificities of the systems described or to the level of detail in the respective models.

The results of (Kiviluoma et al., 2017) showed system cost differences up to 4% between the investment model only and the combination of investment and operational models. The MILP version of the operational model resulted in only slightly higher operational costs than the LP version for all the considered cases with different flexibility options included. The MILP version of the model considered integer unit commitment variables, whereas the LP version used continuously-relaxed and technology-clustered variables. Unexpectedly, the MILP version did not show significant benefits, for example, for the reduced minimum load of thermal power plants. The smallness of the impact was explained by the decreased efficiency when running at still lower minimum loads. It was also acknowledged that the result could change if operational constraints of hydropower were better represented, as hydropower makes a significant contribution to balancing in the Northern European system.

Rather unexpectedly, in most cases the combination of investment and operational models led to lower costs than the investment model alone (Kiviluoma et al., 2017). This was explained to be partly due to the selection of the representative weeks. A similar finding related to the selection of representative periods and decreasing costs with a higher number of representative days was observed in (Frew & Jacobson, 2016) with investment model only (see Section "Level 1A: Operational constraints in investment models"). Yet, the most significant factor affecting the system costs and the estimated benefits of increased flexibility in (Kiviluoma et al., 2017) was concluded to be the ability of the models to capture the impact of flexibility measures. Since the generation expansion planning model omitted several factors that influenced the benefits of flexibility, it gave less reliable results than the operational model.

It can be concluded based on the studies in this category that running the investment model alone, with a coarse temporal resolution and a low level of technical detail, can result in misguided results. The studies highlighted the benefits of explicitly accounting for the chronology and correlation of VG and load in planning. It was also observed that the combination of investment and operational models can lead to lower costs than the investment model alone, for example, if the representative periods in the investment model contain disproportionally more extreme situations. Moreover, the studies indicate that adding detailed unit commitment constraints has less impact on the results than improving the temporal representation from a few representative weeks or a dozen of time slices.

Comparison of other modelling details

Various modelling methods were used for the representation of short-term uncertainty and transmission grids as well as to ensure power system stability and capacity adequacy, but the impact of these differences on the results is more difficult to analyse as there are several factors changing at the same time. Some of the studies took into account the uncertainty of generation and load by using deterministic forecasts and a separate intraday or balancing market in the operational model, whereas some used perfect forecasts. Hart and Jacobson (2011) used day-ahead scheduling and Monte Carlo dispatch simulation in the operational phase to deal with the effect of forecast errors and forced outages. By contrast, various types of reserves were set aside in most of the studies in order to take into account generation and load forecast errors and contingencies. An inertia constraint was included in (Collins, Deane, & Ó Gallachóir, 2017), but the paper did not mention reserve requirements.

DC power flow was included in many of the studies, but also transport models and copper plate models were used. Exchange with countries that were not explicitly modelled was taken into account in (Brouwer et al., 2015) by calculating their residual supply curves and constructing corresponding continuous cost-supply curves. DynELMOD lets the user choose between the transport model and an approach based on the DC power flow model, and these two were compared in (Gerbaulet & Lorenz, 2017). As expected, the flow-based approach resulted in more evenly distributed cross-border interconnection investments and electricity transfers than the approach based on the transport model. The choice between the power grid representations did not have a substantial impact on new generation and storage capacities.

Part of the studies considered a planning reserve margin to ensure capacity adequacy, but also indicators such as LOLE were used to ensure system reliability. A minimum generation capacity for each region was calculated before the investment optimization in (Kiviluoma et al., 2017). The minimum generation capacity was based on the initial net load, and new VG capacity did not contribute to it. The minimum generation capacity requirement is essentially similar to requiring a certain planning reserve margin. In both methods, the modeller needs to decide how to consider the capacity value of VG.

An important observation related to unidirectional soft-linking methods is also the impact of the lack of annual constraints in many UCED models. This was acknowledged in the analysis linking ReEDS and ABB's GridView (Mai et al., 2014; Mai, Sandor, Wiser, & Schneider, 2012). The ReEDS model included constraints to ensure 80% of annual renewable electricity generation in 2050, but the GridView model resulted in roughly 75% share, as its dispatch decisions were based on the cost of generation, and not on the energy source. The annual constraints may also be important, for example, to take account of sustainable use of biomass in energy production.

Level 3A: Bidirectional soft-linking

In the category of bidirectionally soft-linked investment and operational models, not as many studies have been conducted and reported in the literature as in the category of unidirectional soft-linking. However, some examples exist, and we selected three studies for this comparison (see Table 3 and Table 7). In addition, we explore the iterative soft-linking method included in the study by Kiviluoma et al. (2017), presented earlier in Section "Level 2: Unidirectional soft-linking".

Comparison of modelling characteristics

Rosen (2008) soft-linked PERSEUS and AEOLIUS to explore renewable electricity in the European electricity market, while Pina et al. (2013) soft-linked TIMES and EnergyPLAN, and applied the framework to the electricity system of Portugal, with a target to achieve significant reductions in CO_2 emissions. Mills and Wiser (2012) used a generation investment and dispatch model where the investment search algorithm was based on insights from the Benders decomposition method.

Both (Rosen, 2008) and (Pina et al., 2013) considered a time horizon of at least two decades using time slices or time slots. The operational models considered years at full hourly resolution (Pina et al., 2013) or using three representative days per month and an hourly resolution (Rosen, 2008). In (Mills & Wiser, 2012), the time horizon was one year at hourly resolution.

Unit commitment constraints such as start-ups were considered in all three studies. In addition, (Rosen, 2008) considered some other operational details and capacity adequacy requirements: forecasts for wind power and load as well as standing and spinning tertiary reserve requirement were taken into account in AEOLIUS, and a planning reserve margin was included in PERSEUS. Mills and Wiser (2012) modelled the power market using a two-stage process: day-ahead stage for commitment decisions and real-time stage for economic dispatch decisions. Ancillary service requirements and a deterministic day-ahead forecast of variable generation were taken into account in the process.

Feedback links

In the approach by Rosen (2008), PERSEUS first determined the future energy system structure and gave the results as input for AEOLIUS, which then determined the detailed plant scheduling. Fluctuation-induced restrictions observed by AEOLIUS were fed back to the PERSEUS model. Three restriction types were considered: the capacity value of wind power, the additional reserve requirements for wind power, and the efficiency losses in the operation of conventional power plants. The restrictions were used for an improved representation of renewable power production in PERSEUS, helping it to derive optimized and more realistic long-term energy system expansion and operation strategies.

By contrast, a feedback link based on curtailment levels was constructed in (Pina et al., 2013). TIMES provided to EnergyPLAN the installed capacities, and EnergyPLAN results were used to update TIMES regarding the amount of new installed capacity that the system could handle for that year. More specifically, if the curtailment of renewable energy sources was more than 10%, a new combination of capacities was calculated so that it maximized the production from renewable energy sources and did not lead to the curtailment of renewable energy sources exceeding 10%. This defined new capacity limits that were used to update the maximum capacity constraints in the TIMES model for each energy source. While this approach can improve the initial solution, it remains unclear if it converges to the optimal solution. The results showed that if the storage capacity in the electricity system was low, the application of the proposed framework resulted in a significantly different generation capacity mix compared to using the TIMES model only. The main differences were the reduction of the total amount of installed capacity from renewable energy sources, the diversification of the energy sources used, and the earlier investment in more expensive technologies such as solar and wave energy.

The investment search algorithm in (Mills & Wiser, 2012) was based on comparing the short-run surplus and the fixed costs of a candidate set of generators. Short-run social surplus is defined as the difference between gross consumer surplus and the total variable costs associated with all generation capacity in the system. In general, capacity was added when the expected increase in the social surplus exceeded the fixed costs, and capacity was removed when the fixed costs exceeded the expected decrease in the social surplus. In the implementation of the iterative procedure, a candidate set of generators was passed into a dispatch problem and the results of the dispatch problem were used to generate a new constraint in the investment problem. The procedure continued until the set of generators could not be improved. It is described that the procedure usually leads to a set of generators that is in long-run equilibrium but in some cases it fails to converge in the expected manner and alternative techniques are needed to refine the set of generators.

The main modelling framework in (Kiviluoma et al., 2017) was based on one-way soft-linking of the generation planning model Balmorel and the operational model WILMAR. However, the authors in (Kiviluoma et al., 2017) also investigated how the suboptimal planning outcome in the soft-linking method can be partially mitigated by adding artificial costs to the investment model that try to represent the impact of the simplifications made in the investment model. This was done for two different flexibility technology scenarios: heat pumps and batteries. The cost was embedded in the variable operation and maintenance cost of these technologies. In the case of heat pumps, the cost-benefit analysis was not very sensitive to the error caused by the inaccuracies of the generation planning model. The authors concluded that using only a generation planning model or analysing only three representative weeks seems much more influential. Batteries, on the other hand, benefitted significantly from the perfect foresight of the planning model. An artificial cost in the generation planning model suppressed the investments in batteries to a level where the total system net benefits were the highest. Furthermore, the three weeks considered by Balmorel showed relatively more discharging of batteries in the operational model than was present in the full-year results, indicating a bias in the selected three weeks from the perspective of the batteries.

According to the observations, the level of the impact that the bidirectional soft-linking has on the generation capacity mix significantly depends on the system properties. For example, the results from the operational model may not change the generation expansion results much if the system is already rather flexible. In addition, the results from the studies confirmed that representative periods need to be selected carefully, and that the way they are selected can affect the relative value of different technologies seen by the investment model.

Level 3B: Iterative optimization of operation

We found two examples of the use of an operational model together with an investment update algorithm (see Table 3 and Table 7). The first framework is a unit commitment model combined with a perturbation algorithm to update the set of investments and an investment model to provide the initial capacity expansion solution (Belderbos & Delarue, 2015). The second one is the CONTINENTAL model combined with an investment loop, used by the French electric utility EDF (Lopez-Botet et al., 2014).

Comparison of model features

Belderbos and Delarue (2015) compared two approaches to provide initial investment solution: a screening curve method and an MILP-based GEP model with unit commitment constraints. The MILP GEP model considered a one-year horizon using three representative days at hourly resolution. Both initial investment optimization methods in (Belderbos & Delarue, 2015) were combined with a unit commitment model considering full year at hourly resolution. CONTINENTAL also uses hourly resolution, but the initial solution is based on heuristics (Lopez-Botet et al., 2014).

The unit commitment in the operational model in (Belderbos & Delarue, 2015) was based on binary variables, whereas CONTINENTAL uses unit clustering and integer variables (Lopez-Botet et al., 2014). Both models take into account minimum stable generation limits, minimum uptimes and downtimes, as well as start-up costs. To take into account short-term uncertainty and power system stability, both CONTINENTAL and the operational model in (Belderbos & Delarue, 2015) contained reserve requirements. In addition, the simulation of detailed short-term operation is integrated into the CONTINENTAL model by two additional layers that make it possible to test the robustness of the dispatch solutions and to assess the dynamic frequency stability for every dispatch period.

Iterative algorithms

The perturbation algorithm in (Belderbos & Delarue, 2015) consisted of two parts. The first part of the algorithm aimed to subtract units from the estimated set to achieve lower system costs, and the second part of the algorithm aimed to add units. To determine which unit should be subtracted (or added), the algorithm alternately removed (or included) a unit of each generation type and calculated the total system cost of the reduced (or enlarged) sets. In the CONTINENTAL model, the dispatch solution creates a price signal that feeds the investment loop. The iterative optimization with CONTINENTAL ends when all the deployed technologies cover their fixed costs, within a margin of precision, while ensuring that there are at maximum three hours per year with a marginal price that equals VOLL.

A combination of the screening curve method, the perturbation algorithm and the operational unit commitment model was found to have the best performance in (Belderbos & Delarue, 2015). The screening curve methodology provided a good estimation of the optimal set in the least amount of computation time, and the perturbation generally converged to the optimal set. The MILP GEP model provided in general a worse initial estimation and required by far the most amount of time to determine an estimated set. In addition, a perturbation of the set estimated by the MILP GEP model converged in general to a non-optimal set. Using only three representative days in the MILP GEP model was not sufficient to characterize the entire load profile. Furthermore, the variable profile of wind was difficult to capture in three representative days, even more when combined with the fluctuating load.

The authors in (Belderbos & Delarue, 2015) concluded that the basic system planning models can be used as such to provide feasible solutions, but need further adaptation to improve their performance in achieving better solutions. Another observation that the authors made was that the total amount of installed capacity (excluding wind) was approximately equal for all scenarios. When more wind capacity was installed, mid-merit and peaking units replaced part of the baseload generation units.

Compared to the un-rounded generation expansion results of the screening curve method, the perturbation algorithm in (Belderbos & Delarue, 2015) typically reduced the amount of nuclear capacity and increased the amount of oil-firing capacity to arrive to the optimal result. In contrast, the set estimated by the MILP GEP model contained significantly less nuclear capacity and significantly more coal capacity than was optimal after the perturbation. The MILP GEP model also estimated less oil-firing capacity and peak gas capacity compared to the optimal result. The observations highlight the importance to capture operational effects in planning in order to value flexibility suitably, and the necessity to have a realistic representation of the variability of load and VG.

Level 4: Co-optimization

In recent years, a number of approaches to co-optimize investments and operation has emerged. In this category, we selected 13 studies containing investment variables and important operational constraints in a single tool or in tools closely combined using decomposition techniques (see Table 4 and Table 8).

Comparison of model details

The time horizon was several years in part of the studies, whereas other studies were based on a one-year planning horizon. Most of the studies used representative periods. Some of the studies used only 4 or 12 representative days per year, whereas other studies based on representative periods included 3–13 representative weeks per year. Even full hourly resolution was used in some studies to represent a year. Nicolosi, Mills, and Wiser (2010) compared the use of 16–8760 time slices, the most detailed corresponding to full hourly resolution with chronology.

Unit commitment was modelled differently in the studies in this category. Some of them included binary unit commitment variables, whereas others used unit clustering and integer variables to downscale the problem size. Continuously-relaxed and technology-clustered unit commitment variables were chosen in some studies, while the method in (S. Pereira, Ferreira, & Vaz, 2017) was based on quadratic fuel and emission costs, which were assumed to penalize start-ups and shutdowns of thermal power plants and keep the uptimes and downtimes within reasonable limits. The first version of the Resource Planning Model (RPM) is adapted to the power system in Colorado, and it minimizes overall system cost, including capital costs, operations and maintenance costs, fuel costs, and start-up costs during each of the five optimization periods separated by five years from 2010 to 2030 (Mai et al., 2013).

In addition to the temporal representation and unit-related constraints, there were also differences in other modelling details. Transmission grids were represented by using either the DC power flow model, the transport model, or the copper plate model. Capacity adequacy was based on load balance and reserve requirements in most of the studies, but also other methods were used, such as a planning reserve margin, a reliability criterion defined by LOLE, and a reserve margin for each time step. The Resource Planning Model (RPM) uses sequential optimization to allow nonlinear calculations necessary to update the capacity value of VG technologies between the linear optimization periods (Mai et al., 2013). Most of the studies included reserve requirements to cover VG and load forecast errors and contingencies, but there were differences in how the reserves were categorized. In addition to the operating reserve requirements induced by forecast errors, two of the studies considered long-term uncertainty associated with short-term wind power variability using stochastic programming (Jin et al., 2014), (Levin & Botterud, 2015). The formulation of the IMRES model in (de Sisternes, 2014) included reserve requirements, but they were not used in the case study to avoid their impact on the profit calculation (de Sisternes, 2014; de Sisternes, Webster, & Pérez-Arriaga, 2015). All the studies focused on electricity sector only, which highlights the untapped potential to extend the co-optimization to energy system models covering several sectors.

Impact of VG share and value of flexibility

The studies highlighted several significant findings concerning the impacts of VG. When increasing wind power capacity, the unit construction and commitment (UCC) algorithm in (Ma, Silva, Belhomme, Kirschen, & Ochoa, 2013) always selected a more flexible unit than before from a set of three candidate generating units, with smaller minimum output, higher ramp rate, lower investment cost, and higher fuel cost. It was also found that increasing wind share reduced energy prices and increased the prices for operating reserves (Levin & Botterud, 2015). Moreover, the findings of (Koltsaklis & Georgiadis, 2015) highlighted a positive correlation of significant renewable energy share with high natural gas production and electricity trade, offering more flexibility to the power system. Unfortunately, the role of modelling detail in these findings cannot be analysed because the case studies were not repeated with any traditional models.

Storage and electric vehicle flexibility were also shown to have value in VG integration, at least in certain power systems. It was found that, in general, storage decreased total system cost, partially replaced flexible power plants, reduced the curtailment of renewable energy sources, and allowed a more efficient operation of inflexible baseload and intermediate generation technologies (Brijs, van Stiphout, Siddiqui, & Belmans, 2017). Moreover, energy storage was found to bring net benefits in the British power system, while providing services to support real-time system balancing and reducing the need for system reinforcement (Pudjianto, Aunedi, Djapic, & Strbac, 2014). Unfortunately, although the modelling methodology auspiciously combined planning and operational features, the paper did not report many of the important parameters that may have affected the case study results. In another study, electric vehicle flexibility had value in reducing peak demand levels and absorbing wind generation variability, again in the British power system

(Ramírez, Papadaskalopoulos, & Strbac, 2016). The value of electric vehicle flexibility depended on the cost of smart charging infrastructure and users' traveling patterns.

Furthermore, the results indicated that baseload units are most likely to experience revenue sufficiency problems when the share of wind power increases, and new baseload units are only developed when natural gas prices are high and the share of wind power is low (Levin & Botterud, 2015). Levin and Botterud (2015) also compared the effectiveness of different regulatory mechanisms, including scarcity pricing and capacity payments, in ensuring resource adequacy and revenue sufficiency. Without scarcity pricing, no thermal units were profitable. At high wind shares, scarcity pricing was able to ensure profitability for peaking units. In addition, the capacity payments required for baseload units to break even were much higher than for mid-merit and peaking units and increased with the amount of wind power.

Impact of flexibility constraints

The impact of ignoring flexibility and short-term constraints was found to be significant. Palmintier and Webster (2016) demonstrated that considering operational flexibility (inter-hour, reserve, and maintenance constraints) in generation expansion problem results in different capacity mixes. In the cases with 40–60% renewables target, taking into account the operational constraints resulted in a smaller amount of CCGT capacity and a higher amount of wind capacity (B. S. Palmintier & Webster, 2016). Changes were also observed in the gas turbine capacities: in the 40% wind target, gas turbine capacity increased because of the operational constraints, but in the 60% wind target, the operational constraints did not lead to notably increased gas turbine capacity – instead, 52% of wind was curtailed to provide flexibility. In addition, it was found that models with a low temporal resolution may substantially overstate the amount of baseload generation that would be economically optimal under a scenario with a high share of wind energy, while understating the need for peaking and intermediate generation units (Nicolosi et al., 2010). A similar finding was achieved by increasing the temporal resolution in a TIMES model (Kannan & Turton, 2013) (see Section "Level 1A: Operational constraints in investment models").

An interesting observation is that the impact of more detailed operational modelling increased CCGT generation in (S. Pereira et al., 2017) but decreased the need for CCGT capacity in (B. S. Palmintier & Webster, 2016). S. Pereira et al. (2017) applied a mixed integer nonlinear programming model to the Portuguese electricity system and compared the results to a traditional GEP model with less detailed description of operating conditions of thermal units. The authors assumed that quadratic functions for fuel and CO_2 costs should allow to penalize start-ups and shutdowns of power plants and keep the uptimes and downtimes within reasonable limits. The divergence in the results of (S. Pereira et al., 2017) and (B. S. Palmintier & Webster, 2016) may be explained by the differences in the modelling methodologies or in the systems, or it can be related to energy and capacity results not being directly comparable.

The results also indicate that CCGT generation and capacity are particularly sensitive to the changes in the modelling methodologies and system characteristics, as Section "Level 2: Unidirectional soft-linking" also showed that a higher level of temporal and/or operational detail affected CCGT generation differently depending on the study (Poncelet et al., 2016), (Brouwer et al., 2015). In addition, the impact of operational constraints on CCGT investments depended on the assumed fuel costs and the system in question in (Shortt et al., 2013), as was explained in Section “Level 1B: Investment planning using operational models”.

Furthermore, assuming average operating conditions for thermal power plants and neglecting short-term constraints in the planning phase were shown to underestimate system costs (S. Pereira et al., 2017), (Flores-Quiroz, Palma-Behnke, Zakeri, & Moreno, 2016). The results also demonstrated the impact of ignoring flexibility on estimated emissions: the errors will increase with tighter carbon limits and more demanding renewable energy targets (B. S. Palmintier & Webster, 2016). The emission errors from ignoring flexibility were 35–60% for a scenario with a $90/ton carbon tax and a 20% target share for renewables. In addition, omitting operational constraints led to a system that was unable to simultaneously meet demand, carbon, and renewable energy requirements (B. S. Palmintier & Webster, 2016). Additionally, the amount of renewable electricity curtailment and the market value of renewable electricity exhibited noteworthy differences depending on the temporal resolution of the model in (Nicolosi et al., 2010).

In summary, the studies confirmed that operational constraints are important for attaining more realistic estimates for planning outcomes, costs and emissions.

CONCLUSION AND RECOMMENDATIONS

The article has categorized a large number of energy system planning studies and investigated the impacts of modelling methods on VG integration results. For categorizing the planning studies, we proposed a classification with four levels: (1) approaches based on investment models only or operational models only; (2) unidirectionally soft-linked investment and operational models; (3) iterative methods; and (4) co-optimizing investments and operation. Furthermore, we identified a number of challenges associated with the planning problem and high shares of VG: temporal representation, unit constraints, spatial representation and power flow, short-term uncertainty, power system stability, capacity adequacy, energy system integration, and long-term uncertainty.

The studies presented in this paper provide several significant findings related to the impacts of temporal representation and operational detail. Important operational details include power system stability aspects (e.g. operational reserve requirements) and unit constraints (e.g. start-up and shutdown decisions of units). The importance of spatial resolution and extent as well as short-term uncertainty was in focus in a smaller number of studies, and it would be valuable to have more studies focusing on these issues before making conclusive remarks about the results. Long-term uncertainties in energy systems were mostly considered by means of separate scenarios, although there were also methods trying to capture interannual variations in VG time series. Ensuring reasonable and coherent capacity adequacy and taking into account interactions of multiple energy sectors are aspects that require more conscious and transparent methods and wider application.

This review highlights the following two findings. First, using a low temporal resolution or only a few representative days will not suffice in order to determine the optimal generation portfolio in the presence of VG. For example, the results show that when a higher temporal resolution is used in the planning problem, the flexibility of peaking units is better captured and larger investments will be made in them. The chronology and correlation of VG and load are important to be taken into account, and scenario reduction techniques are required for selecting appropriate time series, if a full year or more cannot be used.

Second, considering operational details is important in order to get a more optimal generation portfolio and more realistic estimations of system costs, although they appear to be less significant than improving the temporal resolution. Taking into account operational constraints can have unexpected impacts on the planning outcome, especially when taking into account various policy constraints, such as target shares for renewables or CO_2 limits.

By nature, the modelling approaches were able to deal with the challenges differently. For example, studies relying on investment models did not include operational details such as start-ups and shutdowns of units. On the other hand, they were the only ones systematically analysing the impacts of spatial representation and short-term uncertainty. However, although not analysing the impacts of those two challenges, studies in other categories also applied various methods to take those challenges into account. A remarkable finding is that the most comprehensive methods, i.e. those based on co-optimization of investments and operation, consistently omitted sector interactions and focused on power sector. Thus, there is a clear need for further model development and data acquisition.

The most comprehensive methods become computationally intractable in most practical situations and consequently a trade-off must be made between computation time and modelling fidelity. Model reduction can take many forms and it is not obvious what should be simplified – the review highlights that the choice should depend on the purpose of the planning study. A system planner has different goals than a potential investor: the former is mainly interested in the reliability and cost-effectiveness of the system, while the latter is more interested in revenue uncertainty and profit maximization. Exploring the potential of the most comprehensive methods is needed, at least to understand and confirm which simplifications are least harmful for different purposes. It is clear that operational detail becomes more important at higher levels of VG, as well as the adequate representation of potential flexibility sources – also in other energy sectors.

Moreover, the modeller needs to understand that the benefits and impacts of more advanced modelling techniques on the generation capacity mix significantly depend on the system properties. If the system already has large amounts of flexible capacity, taking into account more operational constraints does not necessarily have a high impact on the planning outcome. Hence, once again, the level of modelling fidelity chosen needs to reflect the questions of interest and the specific characteristics of the system under study.

Finally, although no model is perfect, these are relevant to inform policy and investments in the power sector; hence, it is important for the modeller to make an informed selection of the model and an appropriate interpretation of the results that account for the underlying simplifications and assumptions in each model, as well as the purpose of modelling.

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